Report No. CG-D-20-96, II

Research Methods to Develop Measures of Effectiveness of the United States Coast Guard's Vessel Inspection and Boarding Program

MAIN REPORT - VOLUME II

Timothy Wheeler
Roger Cox
Kishore Gawande
Ryan Stone
Laurie Waisel
William Wallace

Sandia National Laboratories
1515 Eubank S.E.
Albuquerque, NM 87123

FINAL REPORT
May 1995

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National Technical Information Service, Springfield, Virginia 22161

Prepared for:

U.S. Coast Guard
Research and Development Center
1082 Shennecossett Road
Groton, Connecticut 06340-6096

and

U.S. Department of Transportation
United States Coast Guard
Office of Engineering, Logistics, and Development
Washington, DC 20593-0001

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G.T. Gunther
Commanding Officer
United States Coast Guard
Research & Development Center
1082 Shennecossett Road
Groton, CT 06340-6096

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
CG-D-20-96, II		

4. Title and Subtitle
Research Methods to Develop Measures of Effectiveness of the United States Coast Guard's Vessel Inspection and Boarding Program, Main Report - Volume II

5. Report Date
May 1995

6. Performing Organization Code

7. Author(s)
Timothy Wheeler, Roger Cox, Kishore Gawande, Ryan Stone, Laurie Waisel, William Wallace

8. Performing Organization Report No.
R&DC 12/95

9. Performing Organization Name and Address
Sandia National Laboratories
1515 Eubank SE
Albuquerque, NM 87123

10. Work Unit No. (TRAIS)

11. Contract or Grant No.
Z51100-3-E00681

13. Type of Report and Period Covered

12. Sponsoring Agency Name and Address

U.S. Coast Guard	Department of Transportation
Research and Development Center	U.S. Coast Guard
1082 Shennecossett Road	Office of Engineering, Logistics, and Development
Groton, Connecticut 06340-6096	Washington, D.C. 20593-0001

14. Sponsoring Agency Code
Commandant (G-MP)
USCG Headquarters

15. Supplementary Notes COTR and R&DC technical contact is LT C. Rodriguez, 203-441-2848.

16. Abstract

This report describes a methodology for determining the effectiveness of the U.S. Coast Guard Marine Inspection and Boarding Program for deep draft vessels. Measures of Effectiveness (MOEs) were developed at the overall program-wide, major activity, and sub-activity levels.

Econometric analysis was performed on the relationship between the number of personnel and pollution casualties and the resource hours expended by the Inspection and Boarding programs. The estimates provide MOEs by 1) quantifying the decrease in expected number of casualties, and 2) quantifying the increase in the duration in days to a casualty that results from an increase in resource hours. A second methodology called Risk Based Ranking (RBR) was used to enumerate the contribution of factors targeted by sub-activities as being key contributers to the occurrence of casualties.

For U.S. vessels the results indicate that resources expended are effective in reducing expected number of deaths, injuries, and pollution incidents. For foreign vessels the results are not robust and do not allow clear inferences. The RBR showed that the dominant contributors to maritime risk are linked to Drills/Human Factors, Steering/Navigation, and Cargo/Pollution Control sub-activity intervention strategies. The order of these factors varies by vessel service and country of registry.

A prototype decision support system was developed that displays the econometric models graphically. This report is issued in four separate volumes: Volume I - Executive Summary; Volume II - Main Report; Volume III - Decision Support for Utilizing Measures of Effectiveness; Volume IV - Appendices.

17. Key Words

Econometric Analysis	Duration Models
Risk Based Ranking	Decision Support System
Measures of Effectiveness	Marine Safety Boardings
Poisson Models	Marine Safety Inspections

18. Distribution Statement
Document is available to the U.S. public through the National Technical Information Service, Springfield, Virginia 22161

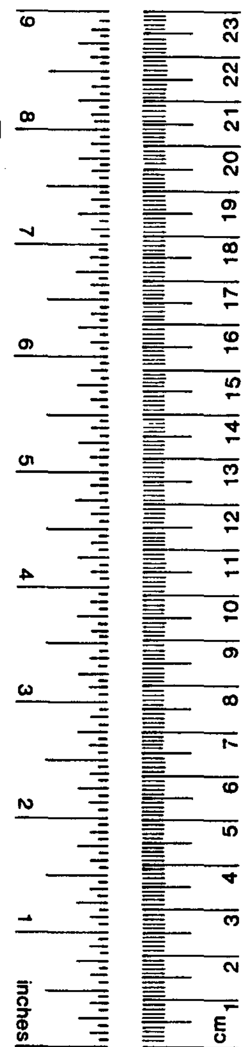
19. Security Classif. (of this report)	20. SECURITY CLASSIF. (of this page)	21. No. of Pages	22. Price
UNCLASSIFIED	UNCLASSIFIED		

METRIC CONVERSION FACTORS

Approximate Conversions to Metric Measures

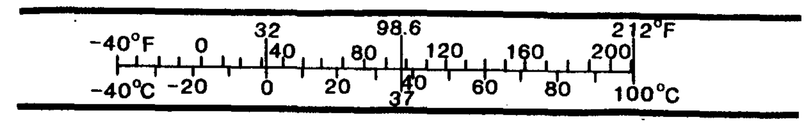
Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	*2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
		AREA		
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
		MASS (WEIGHT)		
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
		VOLUME		
tsp	teaspoons	5	milliliters	ml
tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.8	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
		TEMPERATURE (EXACT)		
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

*1 in = 2.54 (exactly).



Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
		AREA		
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square miles	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
		MASS (WEIGHT)		
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
		VOLUME		
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	0.125	cups	c
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
		TEMPERATURE (EXACT)		
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



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1.0 Introduction

The purpose of this task is to develop informative measures of the effectiveness of USCG intervention activities. The measures of effectiveness (MOEs) should permit the evaluation of various activities within USCG programs to allow a comparison of the relative effectiveness of the program's activities with respect to each other as well as their overall effectiveness in meeting the primary goals of improving the safety and security of maritime transport on U.S. waters.

We propose to use two techniques to construct MOEs for Level I, II, and III activities:

(i) Risk-Based Rankings (RBR) of activities, and
(ii) Econometric Modelling and Estimation of the effect of activities on the occurrence of casualties

This report details the methodology behind these techniques, and reports on the results in developing a three-phased process based on statistical analysis and econometric modeling of existing databases on deep draft vessel casualties and operations. We describe the varying degrees of detail to be addressed to the construction of MOEs for each of the Level I, II, and III intervention activities. Conceptual differences between Level I, II and III activities, require us to tailor our proposed techniques to individually suit them.

This report, in conjunction with a companion volume "Decision Support for Utilizing Measures of Effectiveness", describes the methodology employed and the prototype decision support system developed to aid USCG program management in using the econometric models that generated the measures of effectiveness. In addition, alternative models and displays are presented as well as a discussion of two analytical approaches to resource allocation that employ the measures of effectiveness.

1.1 Level I MOEs

The purpose of Level I MOEs are to provide a high level perspective of the effectiveness of USCG inspection and boarding programs in the promotion of safety and life at sea. The priority at this level is to fundamentally understand how effective the USCG is at the highest level of distinction between the resources expended on the U.S. fleet and resources expended on foreign vessels in U.S. waters. There are two ways to conceptualize Measures of Effectiveness of the entire USCG inspection and boarding programs in the promotion of safety and life at sea.

The <u>first</u> approach is that the USCG inspection and boarding program is an aggregate of several well-defined component activities, specifically those listed as Level II and Level III activities. Under this approach, an assessment of the overall effectiveness of the USCG inspection and boarding program

requires the assessment of the effectiveness of its component activities, and whether resources expended on these activities are being efficiently allocated. The first step is therefore a construction of MOEs for Level II and Level III activities. The second step is to infer the overall effectiveness (Level I) from these component MOEs.

The second approach is to start with the premise that component activity data are just not available, only data pertaining to overall inspection and boarding activities are available, together with data on casualties. It may seem that since the second approach uses much less information than the first approach, inferences from the second approach will be inferior. While this is true if both approaches are used to make the same kind of inferences, we will use the second approach to make a different set of inferences than those we make from the first approach. Examples of the types of inferences are given in Section 2.2.7, once the risk-based ranking and the econometric methodologies have been described in detail.

1.2 Level II MOEs

The next level of perspective on program effectiveness is an understanding of the importance of the principle activities that constitute the deep-draft vessel inspection and examination programs:

A. Inspection Program

1. Certificate Of Inspection (COI),
2. Annual Vessel Reinspection,
3. Hull Examination.

B. Foreign Vessel Boarding Program Activities

1. Annual Foreign Freight Vessel Examinations,
2. Annual Foreign Tanker Vessel Examinations.
2. Annual Foreign Passenger Vessel Examinations.

The distinguishing feature of Level II activities, particularly A1, A2, and A3, is that they are measurable as duration data, for example, time elapsed between a hull exam and a casualty or time elapsed between a COI and a casualty. For this reason the Risk-Based Rankings (RBR) does not apply to these activities. The mapping from these activities to the cause of a casualty is problematic both conceptually as well as in its implementation using the MSMS database. The RBR methodology befits a situation where the cause of the casualty can be attributable with high probability to a particular activity. MOEs for Level II activities will therefore be constructed using the Econometric methodology. A special class of econometric models are used for Level A and B activities above, namely, duration or time-to-failure models.

1.3 Level III MOEs

1.3.1 Definition

Level III establishes a perspective of the effectiveness of inspection and examination sub-activities as defined below:

Level III Inspection/Boarding Activity

1) Cargo Handling/Pollution Control,
2) Steering/Navigation,
3) Document/Paperwork,
4) Drills/Human Factors,
5) Auxiliary Systems (U.S. Flag Only),
6) Power Plant (U.S. Flag Only),
7) Fire Fighting And Prevention,
8) Hull (U.S. Flag Only),
9) Life Saving.

The MSMS database provides information that allows RBRs as well as econometric modelling of Level III activities. In describing the RBR and econometric methodologies we use examples pertaining to Level III activities to make the applicability of the methods immediately obvious. Level II activities fit into the methodology in the same way as Level III activities do, except that the duration-based measure for Level II activities necessitates the use of different estimation techniques.

1.3.2 Risk-Based Importance Measures Of Level Three Inspection/Boarding Activities

An importance measure represents a quantitative estimate of the significance of the contribution made to a quantity of interest. In risk analysis, several importance measures have been defined to assist modelers and decision makers in understanding the potential for effecting change in the risk associated with a process or activity. Risk can be defined as the product of the frequency of an event's occurrence and the outcome or consequences associated with a particular event. A measurement of risk can be combined with a weighting factor that accounts for the level of

significance of Level III inspection/boarding activities to develop a quantitative perspective of each Level III activity's contribution (or "importance") to risk. The combination of a risk measure and a weighting factor of an activity's significance to casualties yields a powerful risk management perspective regarding optimal allocation of resources for affecting the maximum desired change in risk. The importance measures applied here to the Level III inspection/boarding activities are based on the concept of risk-based ranking (RBR) of dominant contributors to risk. The RBR method is developed in [Wheeler, 1993], and is discussed in detail in Section 2.1.

The frequency of maritime casualties can be quantified in different ways for the purpose of developing varied representation of risk. Different representations of risk provide information necessary to achieve different risk management objectives. Two frequencies of maritime casualties were developed for this study:

1) <u>Casualty Frequencies</u> - Casualty frequency rates are defined in terms of the number of casualties associated with a particular unit (e.g., District, MSO) per number of inspections performed by that unit. This enables the occurrence of maritime casualties to be evaluated within the context of the quantity of resources expended specifically on inspection and boarding activities by the USCG at specific units. This frequency offers a perspective of a unit's performance with respect to inspections/boardings relative to other units.

2) <u>Relative Frequencies</u> - Relative Frequencies are defined in terms of the number of casualties associated with a particular unit (e.g., District, MSO) normalized by the total number of casualties occurring within the USCG's jurisdiction. This value establishes a conditional probability that, given that a maritime casualty occurs, it is linked to the inspection activity at a particular unit. This frequency offers a perspective of a unit's contribution to total casualty frequency across the entire USCG jurisdiction.

Frequency rates can be defined at various levels of data aggregation. The highest level would simply be overall casualty frequencies for U.S. and foreign flag vessels, with no distinction between the USCG Districts or MSOs that conduct the inspections. More detailed assessments of casualty data yield casualty frequency rates that are defined in terms of casualty consequences (e.g., pollution, deaths) and the location of the last inspection of a vessel prior to a casualty. The result is a variety of perspectives from which to view the effectiveness of USCG inspection and boarding programs. These two probability measures are discussed in further detail in Section 2.1.2.

The idea of linking a vessel casualty to the last District or MSO to inspect the vessel prior to the casualty should not be confused with identifying that inspection as having failed in its purpose. The casualty reports in the Marine Investigation Module (MINMOD) of the MSMS database are not designed to definitively identify inspection faults or short comings that may have contributed to a casualty. Indeed, the occurrence of undesirable events during vessels operations that contribute to

maritime casualties does not necessarily mean that a potential problem was missed during a vessel inspection. Random failures of ship components and human error can occur even if inspection activities designed to detect such flaws are successful in uncovering problems.

Linking maritime casualties to the USCG units that inspected the vessels does not establish a causal relationship between the inspection and the casualty. However, it does establish an understanding of the importance of specific inspection/boarding activities to maritime risk.

The casualty frequency estimates presented in this report are preliminary and represent an illustrative application of the MSMS database to estimate measures of effectiveness of the USCG's deep draft vessel inspection program for U.S. flag vessels. However, the fundamental method applied for U.S. flag vessels here will also be applied to foreign flag vessels data.

1.4 Decision Support Utilizing Measures of Effectiveness

The purpose of this program element is to provide decision support for those responsible for managing USCG responsibilities in maintaining and improving the safety and security of maritime transport in U.S. waters, in particular the Marine Inspection and Boarding Program. In so doing, it will focus on supporting USCG efforts in the analytic measurement of the effectiveness of their activities. The nature of the program is such that the costs and benefits of the service provided are long term in nature and their output is the prevention of an undesirable occurrence. It is understood that it is difficult to identify a single output measure that characterizes the effectiveness of USCG activities. It is also recognized that data are not available to establish benchmarks or baselines for comparison purposes. Furthermore, the true cost of program activities is difficult to determine due to the multi-mission nature of USCG responsibilities and activities.

However, relative measures of performance can be identified and observed, and the effects of USCG activities designed to affect them analyzed. This effort developed a prototype decision support system in a spreadsheet format that allows USCG program management to use the econometric models described in Section 4.0 for resource allocation. Resource allocation modeling is discussed in Section 5.0.

Another analytical approach is to design an investment strategy to explicitly meet stated goals of the Inspection and Boarding program. Goal programming (GP) formulations set target ranges for the performance in specific program areas. Benefits accrued for achieving the goal are specified as well as penalties for under-achievement and diminished returns for over-achievement. Optimization techniques (e.g., linear programming) are used to decide what combination of activities will best meet the goals, given logistical and budgetary constraints. Section 5.0 presents a GP formulation of the resource allocation problem.

Interaction with the models was done via a "spreadsheet" format. Graphical capabilities of the

spreadsheet format were employed to their fullest extent. Various table shells were proposed for review by USCG management.

The use of the measures of effectiveness in the problem solving and decision making process involved in resource allocation was explored. A simple method using the spreadsheet format and calculating benefit/cost relationships was described. However, this method does not support decision makers in making tradeoffs between various USCG activities that impact marine safety. Two analytical approaches, one using convex resource allocation and the other goal programming were presented with associated advantages and disadvantages. Recommendations were included on implementation of the prototype DSS and resource allocation methodologies.

2.0 Methodology

In Section 2.1 a discussion of the Risk Based Ranking method for the development of Level III MOEs is presented. In Section 2.2 a discussion of the econometric theory and modeling methods to be applied to all of the MOE Levels (I, II, and III) is presented.

2.1 Risk Based Ranking Of Level III Inspection And Examination Sub-Activities

2.1.1 Overview

We will use as examples Level III activities while describing the risk-based-ranking (RBR) and the econometric methodologies. The same method applies to Level II activities, except that the techniques are different owing to the difference in the way Level II and Level III activities are measured. Level II activities are measured as discrete duration and/or count data, while Level III activities are data from a continuously distributed process.

The RBR methodology yields two important pieces of information:

(1) It associates a measure of risk, called Importance, with each Level III activity. This measure of risk possesses a strict definition in this methodology, which is provided below. These risk measures are themselves a valid MOE of each Level III activity. If the risk associated with an activity is low, then that activity may be inferred as being effectively performed. But does that mean that other activities are inadequately performed, or simply that even if the Coast Guard did a perfect job they would still reflect a higher risk relative to other activities? To understand this define Total risk associated with an activity as the sum of its I-risk (Intrinsic risk) and R-risk (Reducible risk), or Total risk = I-risk + R-risk. If one believes that the number of deaths associated with Level III activity "A" could be reduced to zero (so that its I-risk would be 0), then Total risk associated with A would be simply R-risk. Obviously, different Level III activities may have different levels of I-risk, so that the risk-based rankings do not rank on the basis of R-risk which is useful policy information. The ultimate goal is a ranking of activities on the basis of R-risk, but to achieve this we need to make the assumption that all Level III activities possess the same I-risk (which is the case if, for example, all Level III activities have zero or the same base-level of I-risk).

A solution to this problem is to construct measures of risk for Level III activities for each of several years. These risk measures can be normalized by the total number of inspections each year so that the risk measures are themselves comparable across years. Those activities that experience a reduction in the risks associated with them may be inferred as being effective, while those that show

increases may be inferred as being less effective. Those that maintain a fairly constant level of risk may be inferred as having achieved their I-risk levels (unless the Coast Guard is of the opinion that in fact a certain amount of R-risk still remains).

(2) It ranks Level III activities in order of the risk associated with them. The natural inference is that the allocation of resources should reflect the risk associated with each activity. Again, the above comments apply. The solution proposed above is also relevant here. The rankings, however, have the additional use as inputs into decision support, once the econometric estimation is completed. This will be explained subsequently.

2.1.2 Detailed Description of the RBR Methodology

Figure 2.1 describes an event tree for the binning of marine casualties from the MINMOD tables of the MSMS database. This is the first step in the construction of measures of risk and the relative rankings of Level III activities based on those measures. The RBR method is flexible enough to allow any hierarchial structure, and any level of branching or aggregation. However, it is generally useful that the tree be compact enough that the tree itself provides interesting summary information.

Each casualty is binned at the right end of the tree. There is a probability measure associated with each bin. It is possible to use different probability concepts since what is important is the likelihood of a casualty occurring in one bin relative to another bin. Two such measures are:

(a) Relative Frequency of each bin, that is, the number of casualties in a bin divided by the sum total of casualties across all bins. This is the most direct and intuitive probability measure and naturally satisfies norms such as bin frequencies summing to one. In Figure 2.1 and for the example calculations in this section the Relative Frequency measure of bin probability is used. (The probabilities in Figure 2.1 do not sum to one because the events in this tree are not exhaustive. Figure 2.1 contains a selection of a subset of bins from the complete tree, which would include a symmetric expansion of the foreign flag branch. In order to simplify the exposition we have selected only a branch.)

(b) Casualty Frequencies normalize casualties by the <u>number of inspections</u> associated with each bin and therefore add further information that is absent from the Relative Frequency measure in (a). Casualty Frequencies answer the following question: Of the total *inspections* associated with a bin, how many represent the last inspection conducted on a vessel prior to that vessel experiencing a casualty. This measure clearly does not sum to one across all bins, and probably sums to a very small number. Casualty Frequencies can be interpreted as probabilities, but should <u>not</u> be normalized to sum to one. (A sum equal to one implies that an inspection <u>will</u> lead to a casualty.)

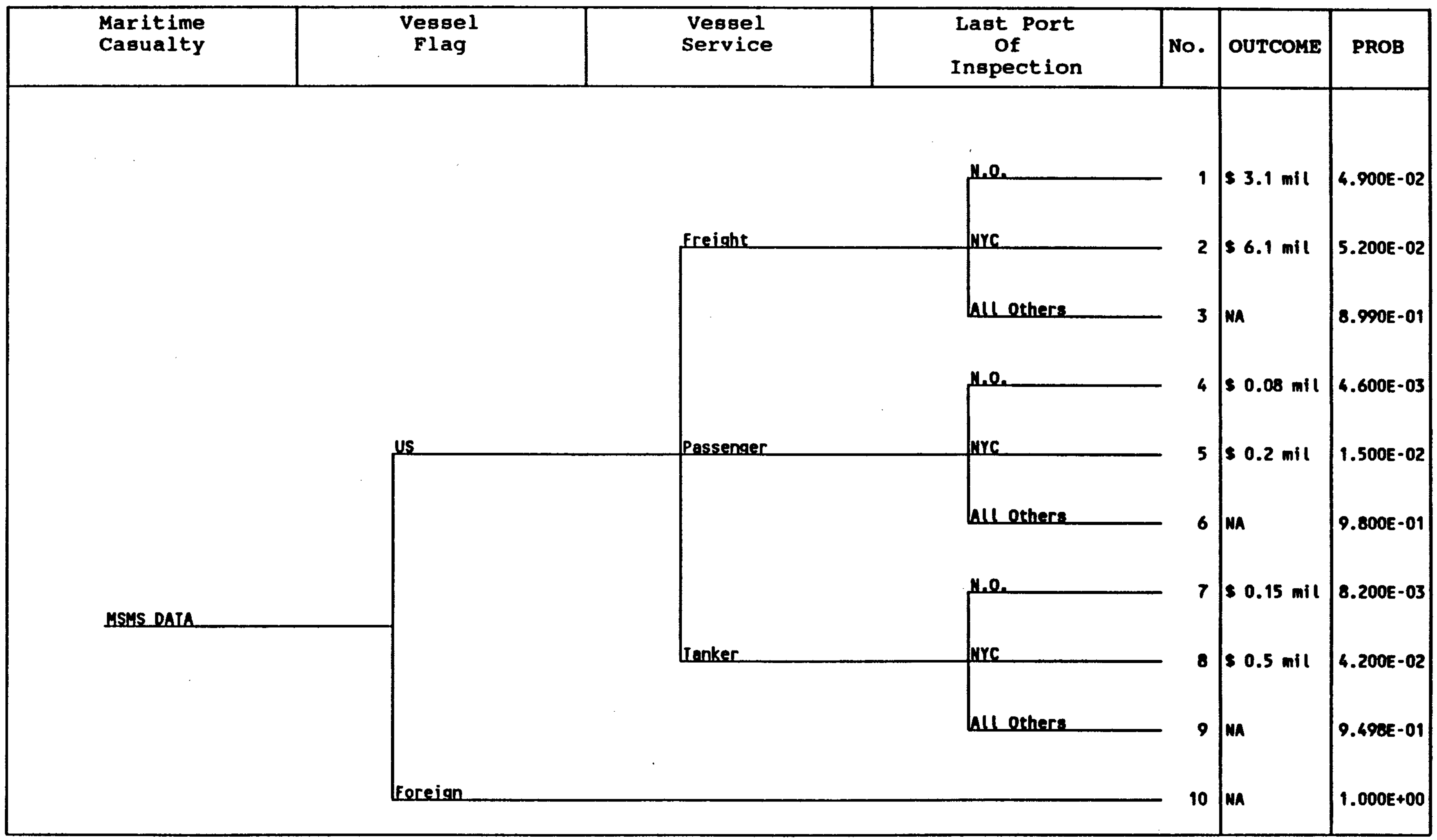

Figure 2.1. Event Tree of Maritime Casualties Referenced to Last Port Of Inspection.

(The Outcome is total damage in millions of dollars. The bin probabilities are the product across the three branches of their probabilities conditional on the preceding branches. For example, P(Casualty is a U.S. Flag Passenger vessel with its last Inspection from N.O.) = P(last Inspection from N.O.|casualty is Passenger vessel with U.S. Flag) × P(Passenger vessel|casualty is U.S. Flag) × P(casualty is U.S. Flag).

The basic difference between measures (a) and (b) is that measure (a) associates damage (loss of life, number of injuries, vessel and/or cargo damage) with a *casualty* while measure (b) associates damage with an *inspection*. The relative likelihood of a bin may differ substantially depending upon which measure, (a) or (b), is used and may lead to different rankings of the importance of Level III inspection/boarding activities to risk.

Define Bin Risk as (Bin Outcome × Bin Probability measure). Bin Outcome may be measured separately as (i) Number of Deaths, (ii) Number of Injuries, (iii) Vessel and Cargo Damage ($), and (iv) Volume of Pollutant Spilled, or a combination of all (in $) or some of these types of casualties. In principle, it is possible to compute separate RBRs for Level III activities for each type of casualty, (i) - (iv). The objective of the RBR is to rank USCG interventions/activities based on Importance of each activity. *An activity's Importance is a statistical measure of that activity's effectiveness* and for activity *j* is given by the sum over all bins of (Bin Risk × Likelihood that activity *j* is associated with that bin).

Table 2.1 and Table 2.2 demonstrate the computation of activity Importance. Suppose four of the nine Level III activities are to be ranked here in this example (a fifth "activity" has been added in this example for completeness):

1. Cargo Handling (CH)
2. Steering/Navigation (SN)
3. Drills/Human Factors (DH)
4. Documents/paperwork (DP)
5. None of the above

In Bin 1 of Figure 2.1 (US/Freight/N.O.), there are 39 casualties out of a total of 7797 casualties involving U.S. flag vessels reported in the CIRT table of MINMOD over the period covered by this analysis (fiscal years 1991, 1992, and 1993). Of these factors relating to CH occurred in 9% of the cases, SN occurred in 20% of the cases, DH occurred in 47% of the cases, DP occurred in 0% of the cases. These probabilities can be defined as cause frequencies. Cause frequencies can sum to more than one because they are not necessarily mutually exclusive in "causing" the casualty. This mapping from USCG activities to bins is key to this task (See Appendix C). We can similarly compute these percentages for each bin. Multiplying the BIN Risk column, element-wise, with the cause frequencies under the activity column in Table 2.1 we get the per bin Importance of each activity recorded in Table 2.2. This information establishes a measure of the contribution of each MSO's various inspection and activities to risk. Summing down Table 2.2 across all bins we get the total Importance of each activity for the entire USCG nation-wide inspection program. The activities can be ranked according to total Importance. A nice feature is that the activities can be ranked by the total Importance of any sub-group bins.

Table 2.1 Computing Bin Importance: Intermediate calculations

Bins	Bin Risk ($)	Cause Frequency [1] CH	SN	DH	DP	None
B_1	151,905	0.09	0.2	0.47	0	
B_2	317,205	0.12	0.13	0.42	0	
B_3	368	0	0.56	0.11	0	
B_4	3000	0	0.7	0.2	0	
B_5	1230	0.13	0.19	0.5	0	
B_6	21,040	0.12	0.15	0.37	0	

Note:

1. Activity columns indicate the Cause Frequency, or proportion of casualties in a bin with which that activity is associated.

Table 2.2 Total Importance of Each Activity

Bins	CH	SN	PP	DP	None
B_1	13,671	30,381	71,395	0	
B_2	38,064	41,237	133,226	0	
B_3	0	206	40	0	
B_4	0	2100	600	0	
B_5	180	234	615	0	
B_6	2525	3156	7785	0	
Importance	54,440	77,314	213,661	0	

Note

- Units are dollars. However, the values are discounted, not absolute. RBRs of USCG activities can be based on subset of rows to assess important MSOs.
- There is information in the *absolute* Importance values and therefore the method yields more than just a ranking. MOEs can even be constructed using Importance values.

The total Importance provides natural MOEs for Level III activities, although this statement must be qualified in light of the comments in (1) of Section 2.1.1. Under probability measure (a), the Importance of activity j may be described as the expected loss associated with a casualty that is attributable to activity j. This is conditional on a casualty having occurred. Under probability measure (b), the Importance of activity j may be described as the expected loss associated with an inspection activity that is attributable to activity j. This is conditional on an inspection (but not a casualty) having occurred. The expected loss can be interpreted as an MOE subject to the caveats of Section 2.1.1. By itself, these measures of expected loss offer little information. But a comparison over time, perhaps yearly, of activity Importance can yield substantial information about whether *risk (expected loss) has been reduced, increased, or maintained by a reorganization of inspection and boarding activities.* This is necessarily a long-term measure of effectiveness, but can be used to assess improvements in the way in which the USCG performs its marine safety activities.

This measure is superior to the more appealing and simpler MOE such as "number of deaths" because it incorporates the randomness that is a distinct characteristic of maritime casualties. For example, each bin has a different probability associated with it. Reduction of risk (as defined by activity Importance) is therefore the objective. We believe measures taken to reduce expected number of deaths (stochastic), say, will work towards the goal of reducing actual number of deaths (deterministic).[1]

2.1.3 Normalization Of Casualty Data and the Concept of an "Inspectible Fleet"

This section contains a discussion on issues related to the identification of vessel exposure to the inspection process. This can be defined as the "inspectible fleet", or the opportunity for performing inspections or examinations on deep draft vessels. Data on the fleet available for inspection is important because it defines the context within which to quantify vessel casualty rates. Three possible approaches are discussed here:

1) number of inspections conducted on the inspectible fleet (used in the preliminary calculations in Section 3.0),
2) number of port calls made by the inspectible fleet between either two successive inspections/examinations or between the last inspection/examination and the occurrence of a vessel casualty, and
3) amount of "vessel time" accumulated by the inspectible fleet (vessel time is defined here as

[1] In the literature in Financial Economics, individual investors seek out a portfolio of assets that maximizes expected rate of return *given* a certain level of variance in the portfolio's returns (or select that portfolio that minimizes the variance associated with a given expected return). Conditionally on the variance, these optimal portfolios form an "efficient" frontier. In this literature, the term "risk" refers to the variance of the portfolio's rate of return. For our risk-based ranking methodology, the term "risk" is used to refer to the expected loss/damage from a casualty rather than the variance of the loss/damage from a casualty.

the total amount of time between either two successive inspections/examinations or the time between the last inspection/examination and the occurrence of a vessel casualty).

The casualty frequencies in the preliminary calculations were estimated by dividing the number of casualties by the appropriate number of inspections performed by the USCG. The number of inspections performed was selected as the denominator for the casualty frequencies because such information provides a basis for vessel exposure to the USCG inspection and examination programs. Other types of vessel exposure data could be used as well. For example, the number of port calls between the occurrence of a casualty and the last inspection prior to the casualty would establish a measure of vessel use that could be used to estimate vessel casualty frequencies. Another approach could be to account for the amount of time between the last inspection and the occurrence of a vessel casualty. However, the latter two approaches it would be difficult to link casualty frequencies to resources committed to inspections and examinations. The first approach incorporates a measure of resources expended on inspections to estimate casualty frequencies in terms of vessel casualties per vessel inspections. The latter two approaches would incorporate a measure of vessel reliability (i.e., amount of vessel use before occurrence of a casualty) to estimate vessel casualties per port call or per unit time.

The first approach establishes a casualty frequency that accounts for all vessel inspections, including those inspections for which no casualty occurs before the vessel receives another inspection. In theory, the same type of information would be desired using either of the latter two approaches, but linking those inspections for which vessels do not experience a casualty prior to the next inspection would require data sufficient to quantify the number of port calls or vessel time in terms of both inspections/examinations for which no casualty occurs prior to the next inspection/examination and for which a casualty does occur.

This illustrates a problem related to linking vessel exposure data to the level of resources committed to inspections and examinations by particular MSOs and Districts. An "inspectible fleet" of vessels must be defined for each MSO and District. The inspectible fleet defines the exposure or the number of opportunities for conducting inspections or examinations. For the approach using port calls as normalizing data, vessel port call data is not contained in the MSMS database. Such data would have to be incorporated into the analysis from the U.S. Army Corps of Engineers' vessel exposure data. However, the Corps of Engineers data is only on U.S. flag vessels. Furthermore, the port call data would have to be related to each relevant vessel casualty record and vessel inspection record in the CIVT and IRIT tables. This could result in an unmanageable task without the benefit of linked databases. In fact, unless specific dates are available for each port call it could prove impossible to correctly link port call information to the last port of inspection. Furthermore, to include those inspections for which casualties do not occur prior to the next inspection, port call data on each vessel inspected at each MSO or District would have to be tabulated so that all port calls could be "assigned" to a specific unit based on the date of each port call and the date of the last inspection prior to each port call. Similarly, for the approach using vessel time as the denominator, it would be

necessary to track the total time between inspections for all vessels inspected at a particular unit that were not involved in a casualty prior to their next inspections or examinations. This would require a very involved querying process of the IRIT records, and it is not readily clear that an accurate compilation of total "vessel time" between inspections or the occurrence of a casualty could be compiled for the inspectible fleet for each USCG unit.

The method of normalizing casualties by the number of inspections performed offers the most direct way to link the occurrence of casualties to the inspecting USCG units and to link the "successful" outcomes (i.e., all vessel inspections/examinations for which no casualty occurs prior to the vessel's next inspection/examination). However, unlike the other two methods, which incorporate a measure of vessel safety performance into the quantification of casualty frequencies (i.e., amount of safe "vessel time" or number of successful port calls), this method only establishes safety within the context of resources committed to the inspection/examination programs. If such information is not carefully evaluated it would be possible to arrive at erroneous conclusions regarding vessel safety. Suppose that at a particular USCG unit the decision was made to double its rate of examinations over past practice. If the number of casualties that occurred from the set of all vessels examined by that unit were to remain constant (or even increase) compared to the past, then the resulting casualty frequency would be lower than the casualty frequency estimated from past data, despite the fact that the actual number of casualties remained constant. However, meaningful insights could readily be gained from the data by studying the change in casualties compared to the change in resources committed to examinations. Furthermore, the concept of an "inspectible fleet" is important here. In the example here, the USCG unit "decided" to double the rate of examinations. Current USCG policy allows each MSO to determine which foreign flag vessels that call within a unit's jurisdiction should be examined. Furthermore, these same foreign flag vessels could potentially be examined at any port call. Hence, for a foreign flag vessel casualty it could become unclear as to which MSO unit the casualty should be "assigned". For the U.S. flag fleet, the concept of an inspectible fleet is much more clearly defined, especially if only periodically prescribed inspections such as the COI, the Annual Reinspection, and the Hull inspection are used as the inspection benchmarks. U.S. vessels receive these inspections based on regulated time periods. Thus, the number of such inspections conducted by a particular unit cannot be increased or decreased based on a decision of the local unit. For this situation, the number of inspections establishes a sound basis for evaluating the success of inspections. As in the example above for foreign flag examinations, suppose that the rate of U.S. flag inspections was increased based on a new prescribed schedule. If the actual number of casualties associated with vessel inspections were to remain the same for such a situation, then the resulting decrease in casualty frequency would provide valuable insight into the benefits of increasing resources for inspections since the number of inspections would provide a true indication of the inspectible fleet.

2.2 Theory and Methodology of the Econometric Modelling of Level I, Level II, and Level III USCG Activities

This section is comprised of the following sub-sections:

- 2.2.1 The behavioral theory underlying the estimating equations.
- 2.2.2 The econometric specification of the estimating equations, and the main issues.
- 2.2.3 Econometric problems inherent in (ii) and data problems
- 2.2.4 Robust and sturdy estimation of the main issue/s.
- 2.2.5 Level III MOEs.
- 2.2.6 Level II MOEs.
- 2.2.7 Level I MOEs.

2.2.1 The Behavioral Theory

The theoretical ideas borrow heavily from the work on monitoring oil spills during oil transfers contained in Epple and Visscher (Epple, 1984) (henceforth EV). We have applied the EV theory to the case of marine safety, particularly USCG activities devoted to monitoring and controlling casualties associated with deep draft vessels. A behavioral model forms a strong foundation for the empirical analysis. Changes in the behavioral model must be accompanied by changes in the empirical analysis. A formalization of the behavioral model provides not only a framework for the empirical analysis but brings to fore the key issues which need to be resolved by means of the empirical analysis.

Here we formally model the problem that the Coast Guard faces in its inspection and boarding activities. We believe a principal-agent model which brings out the agency problem that the Coast Guard must solve, is the appropriate model here.

The principal-agent problem is a well-known one in regulatory economics. A typical example is as follows. The *principal*, the manufacturer, has its *agent*, the distributor, sell its products. The manufacturer cannot perfectly observe the sales effort of the distributor and realizes that its agent may try to take advantage of the principal's incomplete information about the agent's actions. For example, the distributor may advertise less than it is supposed to, in order to save money and thus *free ride* on the manufacturer's reputation. Free-riding occurs when one firm benefits from the actions of another without paying for it. In this example, the problem is to design an optimal contract that prevents free-riding. That is, the contract offers the *same* incentive to the agent to maximize sales as the principal possesses. That is, it is as if the principal itself were doing the distribution (agency's job). The failure of designing such optimal contracts is often advanced as a reason for vertical integration by firms. Principal-agent problems are the main economic reason why centrally planned economies (eg. Russia) are highly inefficient and wasteful.

The manufacturer-distributor example is simplistic. A more realistic scenario is where the outcome (sales) is a random variable, with a range of possible outcomes, each with a distinct probability. The agent can affect these probabilities - favorably by taking action desired by the principal, and

unfavorably by not doing so. The problem is compounded by the fact that usually the principal has no way of telling whether the agent actually took the desirable action or not. He can only infer that from the realized outcome. This is probably the case with the Marine Inspection and Boarding program.

The counterpart to free-riding in the case of the Marine Inspection and Boarding Program (the USCG is the principal) is shirking or concealing their vessel inadequacies by vessel owners (the agents). The problem is to design an optimal monitoring/inspection/enforcement strategy to minimize shirking. The idea is to have shipowners behave in the same manner as would the USCG if *it* were in charge of operating the vessel. That is, most casualties then would be as close to random given attributes beyond the USCG's control, such as the weather, etc.

Epple and Visscher (Epple, 1984) and Cohen (Cohen, 1987) apply this theory to econometrically model oil spills and design a strategy to prevent them. Their data is for approximately 4500 spills between 1974-1977, and both papers voice concerns about data inadequacy. The methodology employed for assessing Level II and Level III USCG activities is based on the theory in the Epple and Visscher and the Cohen papers. We have made some modifications to their statistical assumptions, and we estimate a broader range of specifications to check for the robustness of the results.

Here we present a summary of the principal-agent models as applied to the Marine Safety program. The objective of this exercise is to provide a basis for the empirical analysis, or more specifically, provide a foundation for the econometric specification. That is, the statistical model, the choice of variables in that model, and what inferences the model may allow on the basis of theory.

I. Deterministic variables

(i) Agent incurs expenditures M1 and M2 to prevent a casualty.

Eg. $M1_T$: expenditure to reduce probability of spill
$M2_T$: expenditure to reduce size of spill
$M1_P$: expenditure to reduce probability of casualty
$M2_P$: expenditure to reduce intensity of casualty (deaths/injuries)

Assume M1 does not affect M2

Eg. M1 = installation of sophisticated navigation equipment
M2 = training crew to reduce damage given casualty occurred

(ii) **Z1** and **Z2** are sets of exogenous variables affecting casualty.
Note that $\mathbf{Z1} \cap \mathbf{Z2}$ may be non-empty, or $\mathbf{Z1} \subset \mathbf{Z2}$, or $\mathbf{Z1} \supset \mathbf{Z2}$, or both.

Eg. Z_T = {Vessel size, Price of oil, Vessel age, Vessel design, Waterway, Weather}

(iii) W = Coast Guard enforcement effort

(a) Total number of inspection hours
(b) Number of inspection hours by Type II activity (W is a vector)
(c) Type of inspection (Binary indicator): COI, Hull, etc.

II. <u>Random variables</u>

(i)

$$R = \begin{cases} 0 & \textit{if no casualty occurs} \\ 1 & \textit{if casualty occurs} \end{cases}$$

(ii)

$$S = \begin{cases} 0 & \textit{if casualty undetected } R=1 \\ 1 & \textit{if casualty detected } R=1 \end{cases}$$

(iii)

$$A = \begin{cases} 0 & \textit{if nopenalty assessed } R=1,\ S=1 \\ 1 & \textit{if penalty assessed } R=1,\ S=1 \end{cases}$$

(i) $\mathrm{E}(R) = \rho(\underset{(-)}{\mathrm{M1}}, \mathbf{Z1})$

(ii) $\mathrm{E}(S) = \psi(\underset{(+)}{\mathrm{W}})$

(iii) $\mathrm{E}(A) = \phi(\underset{(+)}{\mathrm{W}}, \underset{(+)}{\mathrm{X}})$

Note:

(a) See (Cox, 1993) for flow chart information on probability of shirking by agent.
(b) S is important since if Prob(S=0) is high then agent will not fear the consequence (legal, monetary) of shirking or concealing information leading to effective inspection by principal.
(c) R, S, A describe three distinct events, and the need for modelling these events separately is clearly seen in the case of oil spills (Epple and Visscher).
(d) Dependence of mean of S on just W and of A on W and X.

(iv) X = Intensity of casualty

(1) Tankers: Spill size
(2) Freighters: Cargo and environmental damage
(3) Passenger: deaths/injuries

$\ln X \sim \text{Normal}(\mu, \sigma^2)$, where $\mu = \mu(\text{M2}, \underset{(-)}{\mathbf{Z2}})$

The signs below the variables indicate expected signs on coefficients on these variables.

(v) P.X = direct cost of casualty

(1) Tankers: (P of Oil × X) + Vessel damage
(2) Freighters: (P of Cargo × X) + Vessel damage
(3) Tankers: (P of Life × X) + Vessel damage

(vi) H = \$ penalty, or \$ legal costs, or \$ other action (eg. cleanup of spills)
Let H be termed "Penalty costs", and let these costs be a function of X.
$H = H(X) = c0\, X^{c1}$

This is a "constant elasticity" cost: a 100% increase in X leads to a c1 % rise in H.
c0 and c1 are parameters that can be estimated.

Then, the *casualty-related cost* to the agent, K, is given by

K = *R.S.A* (H) + *R*.P.X + M1 + M2 (*)
= (Prob of getting hit by H)×(H) + (Prob of casualty)×(Direct cost of Casualty) + prevention expenditures (decision variables M1 and M2)

Note: K is a random variable, since X is also.

Agent chooses M1 and M2 to minimize E(K), since M1 reduces *R* and M2 reduces X and *A* (and possibly *S*, but here assume not). To get E(K) need to specify probability distribution of random variables in (*): (*R*, *S*, *A*, X) (see above)
Now we can write E(K) analytically as

$$E(K) = \rho(\text{M1}, \mathbf{Z1}).\ \psi(W).\ \phi(W, X).\ c0 \exp\{c1\ \mu(\text{M2},\mathbf{Z2}) + c1^2\sigma^2/2\}$$
$$+ P.\ \rho(\text{M1}, \mathbf{Z1}) .\ \exp\{\mu(\text{M2},\mathbf{Z2}) + \sigma^2/2\} + \text{M1} + \text{M2}$$

Choose M1 and M2 at $M1^*$ and $M2^*$, respectively to minimize E(K) to get
$M1^* = G1(W, \mathbf{Z1}, \mathbf{Z2}, \sigma^2)$, and
$M2^* = G2(W, \mathbf{Z1}, \mathbf{Z2}, \sigma^2)$,

From these we get expressions for (1) mean casualty frequency, and (2) mean casualty intensity

$$E(R) = \rho(W, \mathbf{Z1}, \mathbf{Z2}, \sigma^2) \qquad (**)$$
$$E(\ln X) = \mu(W, \mathbf{Z1}, \mathbf{Z2}, \sigma^2). \qquad (***)$$

These form the basis for the econometric analysis.

Notes:
(1) These equations are "reduced form" equations. The economic logic for inclusion of variables is not directly obvious from the equations themselves. The logic must go through the "structural model" upon which the reduced form is based. For example an increase in Coast Guard effort, W, increases probability of detection, probability of a penalty, and size of the penalty. This,in turn, leads the agent to increase M1 (and/or M2) that should leads to reduction in E(*R*) (and/or E(ln X)).

(2) σ^2 enters because of the log-normality of X. This is unobservable and may cause problems in the estimation.

2.2.2 Econometric Specification

The following models are theoretically possible in the estimation of equations E(*R*) in (**) and E(ln X) in (***) above (see Greene, 1993 for technical details on their estimation): [2]

(i) (**) Probit/Logit with rhs variables in levels
(**) Probit/Logit with rhs variables in logs of levels

(ii) (***) Linear with lhs and rhs variables in logs of levels
(***) Poisson model
(***) Duration model

We estimate the function E(*R*) (probability of personnel and pollution casualties) using the Probit model and E(ln X) (number dead and missing, number injured, number of pollution incidents) using both, a Poisson model, and a Duration model.

The general specification is as follows:
$\text{lhsvar} = f(W, Z1, Z2, \sigma^2)$

---

[2] See e.g. William Greene's text, Econometric Analysis, Macmillan, 1993, for technical details pertaining to these and other econometric models.

For the E(R) function, lhsvar is a binary indicator of casualty occurrence. Estimation is by a nonlinear Probit model (that keeps the prediction between 0 and 1). In principle we can use more than 2 levels, eg 5 levels of intensity of the casualty (ranging from "Not serious" to "multiple deaths") and can model them as Ordered Probit.

For the E(ln X) function, we use a Poisson model because the number of incidents is usually a small number (usually less than 10), and the outcomes are thus easily modelled using a discrete distribution such as the Poisson. Time-to-casualty is the lhs variables in the analysis of Level II activities, and Duration models are employed for that purpose.

The issue of interest is the coefficient on W. W can be a scalar (total inspection hours, total boarding hours), or a vector (hours for each Level III activity).
Inspection hours are obtainable from table CRST, and type of inspection from IRIT.

Z1 and **Z2** can theoretically include the variables such as Vessel size, Vessel age, Kind of waterway (qual.), Weather (qual.) Vessels of different service may require the inclusion of different variables. For example, for Tankers the price of oil may be included, for Freighters the price of cargo, and for Passenger the number of passengers. But our choice of variables is restricted to data available from the MSMS database.

2.2.3 Econometric Problems

(1) The presence of σ^2 is a problem. Epple and Visscher propose an ad hoc solution to this and though it is possible to implement their solution here, we do not do so. It is the lognormality of X that causes σ^2 to appear on the rhs, but since we do not use a lognormal model for estimation (we use a Poisson model), we hope the problem is resolved. In any case, we feel that ignoring this problem will not qualitatively affect our results.

(2) Different assumptions about the prob. distributions of r.v.'s lead to different *functional forms* of ρ and μ. Doing so is cumbersome and most probability distributions will not lead to closed-form analytic solutions for E(R) and E(ln X) anyway. Hence, instead of deriving functional forms for each assumption about the r.v.'s, we experiment with different reduced forms as outlined in Section 2.2.2.

(3) Our feeling is that there is a lot of randomness about the occurrence and intensity of casualties. This is good and bad. If the lhs variable (number of personnel and pollution casualties) showed great range and variance, we would be very confident of getting strong estimates on **Z1** and **Z2**. But imagine that the USCG is doing a perfect job. Then W would pick up very little if anything, since the accidents are purely random (or purely random conditional on **Z**). Our feeling is that USCG is not perfect, and hence W will indicate sources of improvement. But there will be enough noise and randomness that the equation is probably not going to have a strong measure of fit.

2.2.4 Robust and Sturdy Estimation

We will perform the following in order to investigate the fragility or robustness of the econometric estimates. The data for the regression model is a matrix with N "observations" (rows) and K+1 "variables" (columns), where K is the number of variables on the right-hand-side (rhs variables are termed "independent variables", and the lhs variable is the "dependent variable") of the E(R) and E(ln X) equations.

(i) Sensitivity to outlier: Block-at-a-time deletion of observations and inspection of resulting estimates to see whether there are influential "outliers" driving the results.

(ii) Exogeneity of variables: This problem arises if a rhs variable is not truly an independent variable. An example is where the numbers of hours spent on an inspection is higher precisely because that vessel has a higher *a priori* likelihood of casualty. Hence the number of activity hours is itself "caused" by the probability of occurrence of a casualty, and, simultaneously, the number of activity hours act to reduce the probability of occurrence of a casualty. This is the well-known problem of simultaneity or "endogeneity of regressor" in the econometric literature. The estimated models will be tested for regressor endogeneity where possible. (This is not a simple task for nonlinear models like the ones we propose to estimate.)

2.2.5 Level III MOEs

(i) The coefficients on W, where W is a vector with each element representing the amount of a Level III activity, are natural measures of effectiveness. They answer the question of how much the lhs variable (e.g. number of injuries) will decrease if an element of W (that is, a specific Level III activity) were to increase marginally or, conversely, how much the lhs variable will increase if an element of W were to decrease marginally. It must be emphasized that these are estimates for marginal changes, not large changes that push the hypothetical values of the W variables outside the "range of experience".

(ii) The above coefficients can be used for simple but very informative cost-benefit analysis. For example, suppose W, a scalar, measures the number of total inspection hours, and lhs variable is number of deaths. The coefficient on W tells the effectiveness of an increased W in reducing the number of deaths. Suppose 100 additional hours of W reduce deaths by .1. If the cost of 100 additional hours of W is less than (.1 × 2,500,000) then increasing W is effective in terms of this simple cost-benefit analysis.

(iii) It is possible to use the Bin Risk (Bin probability × Bin consequence) in the RBR method as a dependent variable (which takes the value zero if there is no casualty) in the econometric analysis. This would point out how much "expected loss" can be reduced by different Level III activities.

These could usefully supplement the analysis in Section 2.2.2, but at this stage we expect this to be secondary to those results.

It is to be noted that while the econometric analysis yields useful MOEs, the use to which they may be put depends on the RBRs. The econometric analysis tells us what could happen due to changes in Level III activities, but does not offer a clear answer to the question of which activities *should* be changed, given a budget constraint. The RBR usefully supplements the econometric results by indicating those activities that are most frequently associated with undesirable consequences of casualties. If it turns out that the activities with the highest risk-based rank are also those that the econometric analysis points out to be the most economically significant (large), then the policy conclusion is unambiguous. A conflict between the RBR and the econometric results can arise when, for example, the econometric analysis concludes that an increase in activity A can significantly lower casualties while the RBR analysis ranks activity A low in its ability to reduce the risk of casualty. In this case we need to resolve the conflict within a budgeting or programming framework where the marginal costs of (increasing) each activity and a budget constraint are explicitly spelled out. The Resource Allocation model in Section 5.2.2 is one such model that achieves this.

2.2.6 Level II MOEs

As mentioned in Sections 1.2 and 2.1.1, the essential difference between Type III and Type II activities is the way in which we measure them. Level II activities (labelled "A" and "B" in Section 1.2) are measured as "duration" data, that is, time elapsed between an activity and a casualty. This is how the variable W is measured in the econometric analysis of Level II activities. The appropriate technique for estimation is duration models or time-to-failure models. The underlying theory is the same as proposed in Section 2.2.1, and the form of the estimating equations is the same as proposed in Section 2.2.2. The conclusions are interpreted similarly as in Section 2.2.4 for the Level III activities, except that these MOEs now answer the question of how adversely a longer time period between inspections may affect the probability [E(R)] of occurrence and the intensity [E(ln X)] of a casualty.

It is to be noted that if there is sufficient variability in W then statistically significant estimates, and hence meaningful MOEs, are possible. Since U.S. flag vessels are required to undergo major inspections (i.e., COI, Annual Reinspection) over fixed periods, W does not vary adequately (except of course for the casualty cases, where the time from the last inspection to the casualty probably varies widely across casualties). The time between Hull inspections may show greater variance since the requirement does not stipulate an exact time between two such inspections.

2.2.7 Level I MOEs

For the purpose of describing the construction of Level I MOEs, recall the discussion in Section 1.1 about the two approaches to achieve this.

(i) The first approach is to make an assessment about the overall effectiveness of the marine safety and inspection program from the Level III and Level II MOEs. One way to assess this is to obtain econometric estimates annually, say, over 10 years. If the level III MOEs [from Section 2.2.5 (i)] show a consistent improvement (coefficient on most elements of the vector W decrease over the years), then we may conclude that the program is succeeding in achieving its marine safety goals. The difference between using econometric analysis to conclude this, rather than using a naive indicator such as the actual number of deaths, or injuries, or damage, is that the econometric analysis *controls* for influences outside the ability or purview of the Coast Guard program, that is, factors that contribute purely to I-risk (see Section 2.1.1), and focuses on what the Coast Guard program can achieve by way of reducing R-risk (see Section 2.1.1).

(ii) The second approach is to make an assessment about the overall effectiveness of the marine safety and inspection program from aggregate information. While the RBR method does not apply anymore, the econometric methodology is applicable. Two methods are theoretically possible here:

> (1) In the econometric analysis, simply use W as a one-dimensional (scalar) variable that measures total inspection effort, or total boarding effort. Then construct MOEs just as for Level III activities as described in Section 2.2.5.
>
> (2) Use Casualty Frequency rates as the dependent variable in the econometric analysis. Essentially, think of the following experiment. We would like to see an experiment where we could change resources expended on various kinds of inspections, and observe the effect on the occurrence of casualties. Such an experiment exists, although unlike a lab experiment, where we can isolate other factors which may cause "disturbances" in the occurrence of casualties, the existing experiment is not so controlled and therefore the data from it contains a lot more noise in addition to information. Inspections categorized by MSO provides such an experiment. To make MSOs comparable, we normalize by the number of inspections, and therefore obtain Casualty Frequencies. These have been tabulated in great detail and offer a variety of information. However, by themselves they may not point to "weak" MSOs simply because there may be more noise (outside factors causing casualties, rather than some deficiencies at that MSO) than information (casualties that could be prevented by improving the quality and quantity of inspections). The econometric methodology tries to isolate the factors causing the noise and hence make the relevant inferences from the actual information in the data. It is possible to do an econometric analysis for each MSO and then compare MSOs for their overall effectiveness. We propose to pool the Casualty Frequency and other data across MSOs, and then estimate the effect of a change in W on the Casualty Frequency (using other variables to isolate out the noise). Doing this estimation annually over several years of data can indicate, as in (i) above, whether the Coast Guard is improving over time

in achieving its overall marine safety goal.

In the econometric analysis presented in Section 4, we implement method (1) in great depth, but do not implement method (2). This is a probably rewarding approach, and we leave its implementation for the future.

[BLANK]

3.0 Risk-Based Ranking Analysis

3.1 Application Of Risk-Based Ranking Method to the MSMS Data Base

Risk-Based Rankings, or RBRs, were developed to establish an understanding of the importance of the Level III U.S. flag (inspection) and foreign flag (boarding) intervention strategies. Level III intervention strategies are summarized in Table 3.1.

Table 3.1 Level III Inspection/Boarding Activity

	Intervention Activity	Intervention Program*
1)	Cargo Handling/Pollution Control,	Inspection/Boarding
2)	Steering/Navigation,	Inspection/Boarding
3)	Document/Paperwork,	Inspection/Boarding
4)	Drills/Human Factors,	Inspection/Boarding
5)	Auxiliary Systems,	Inspection
6)	Power Plant,	Inspection
7)	Fire Fighting And Prevention,	Inspection/Boarding
8)	Hull,	Inspection
9)	Life Saving.	Inspection

* Even though Activities 5,6,8, and 9 are associated with the U.S. flag Inspection program only these activities were included in the foreign flag RBR analyses since the MSMS MINMOD CEVT records use the same set of casualty cause keywords for U.S. and foreign flag vessels.

Aggregation of Data

Data was aggregated and analyzed at three different USCG "Unit" levels for both inspection and boarding activities; the whole USCG as a single unit, each USCG District, and each MSO. Figures 3.1, 3.2, and 3.3 illustrate the logic by which MSMS MINMOD casualty data was characterized to aggregate the data for the three different unit level perspectives.

The highest level of data aggregation is to simply distinguish between the U.S. flag ships and foreign flag ships. Figure 3.1 shows how casualty data is aggregated to define the bins and calculate the relative frequencies and casualty frequencies by U.S. or foreign flag. The logic diagram of Figure 3.1 is simplified for illustration purposes. The structure shown in Figure 3.1 for U.S. flag vessels would be repeated for foreign flag vessels. Casualty reports from the

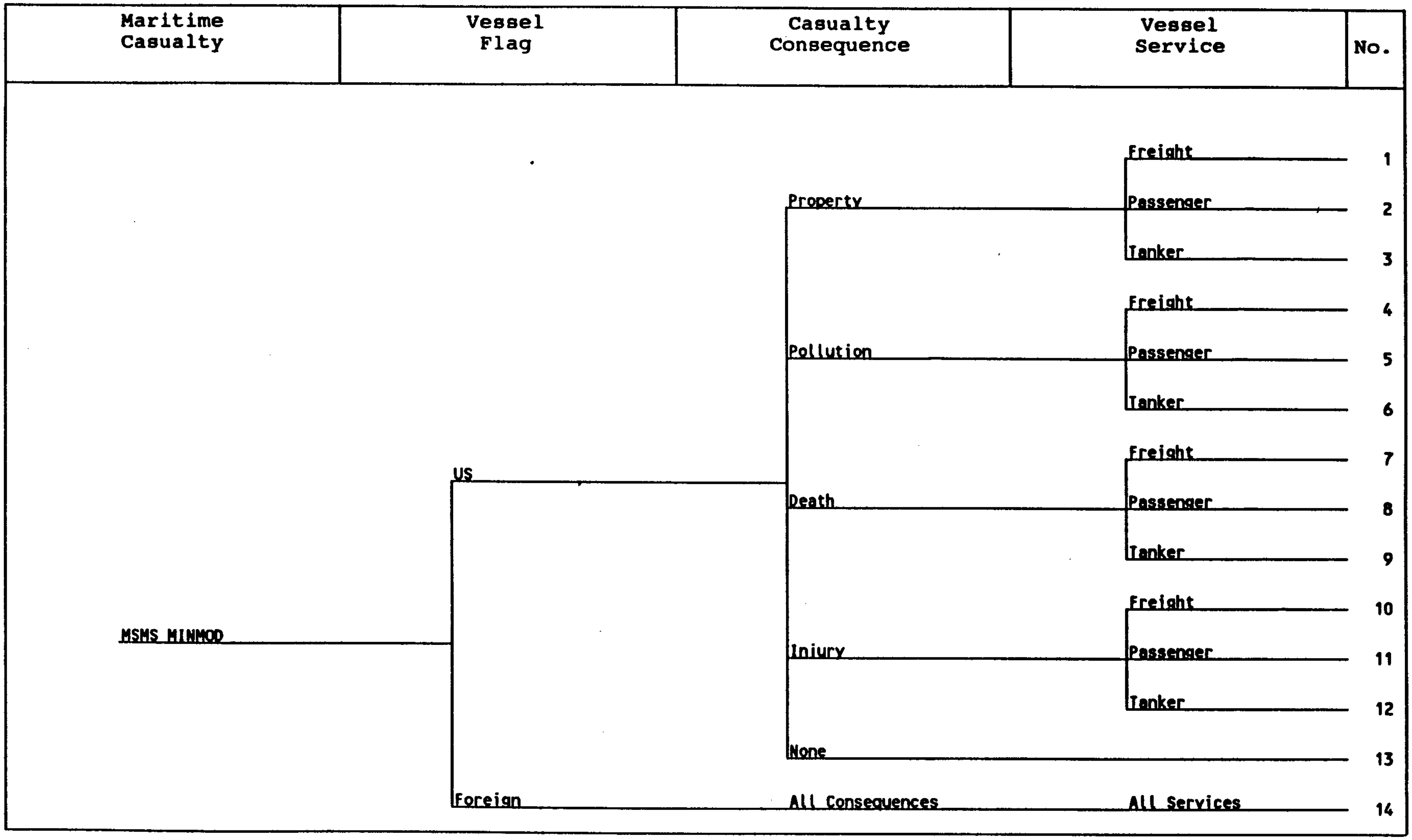

Figure 3.1. Data Aggregation Logic For U.S. Versus Foreign Flag Deep Draft Vessels.

Maritime Casualty	Vessel Flag	Casualty Consuquence	Vessel Service	Last District Of Inspection	No.
MSMS MIMMOD	US	Property Loss	Freight	Dist 1	1
				Dist 2	2
				Dist 5	3
				Others	4
			Passenger	Dist 1	5
				Dist 2	6
				Dist 5	7
				Others	8
			Tanker	All Dists	9
		Pollution	All services	All Dists	10
		Death	All Services	All Dists	11
		Injury Only	All Services	All Dists	12
		None			13
	Foreign	All Consequences	All Services	All Dists	14

Figure 3.2. Data Aggregation Logic For USCG Districts For Deep Draft Vessels.

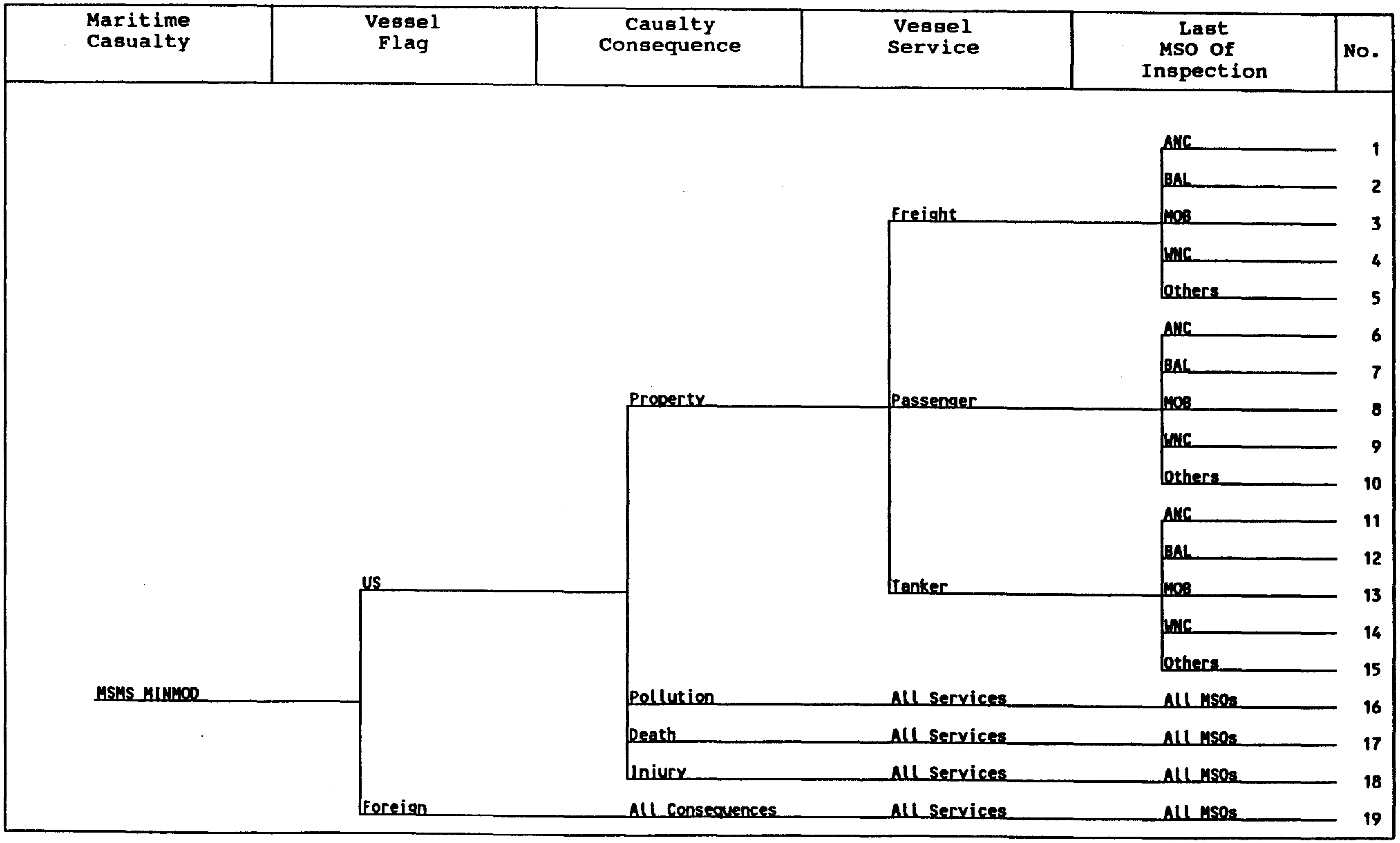

Figure 3.3. Data Aggregation Logic For USCG Marine Safety Offices For Deep Draft Vessels.

Casualty Investigation Report Table (CIRT) of MSMS MINMOD are aggregated into groups or "bins" that represent the various outcomes of the logic tree. This binning process is accomplished by designing queries of the MSMS database that identify the appropriate logic tree casualty and vessel characteristics that are relevant to each CIRT record so that each record is "tracked" to the appropriate bin. For example, path 1 characterizes all freight casualties, path 2 all passenger vessel casualties, and path 3 all tanker casualties involving U.S flag vessels where property loss was a consequence of the casualty. The detailed queries that were developed to assign vessel casualties to the various bins and to count the number of inspections performed by each relevant USCG unit are in Appendix B.

It is important to understand that the outcomes of the logic trees in Figures 3.1, 3.2, and 3.3 are not necessarily mutually exclusive. The trees are designed to define various ways in which the data can be aggregated to achieve different perspectives on maritime safety. Thus, any single CIRT record might be filtered into more than one outcome and be incorporated into the estimates of multiple casualty frequencies depending on the characteristics of the casualty. For example, any CIRT record for a vessel casualty that resulted in one or more deaths and property loss would be filtered through both the "Death" and "Property Loss" paths in Figure 3.1. This does not constitute double counting of casualties because the relative and casualty frequencies are separately estimated for each type of casualty (e.g., death, injury, property loss). Thus, the binning of MINMOD casualty data as depicted in Figure 3.1 represents four distinct RBR analyses, one for each of the specific consequences chosen for this analysis; property loss (in dollars), pollution (in gallons of pollutant spilled), number of deaths, and number of injuries. These analyses provide four distinct perspectives by which the casualty data can be aggregated to achieve an understanding of maritime safety.

Summary of Risk-Based Ranking Analyses

For each intervention activity regime (U.S. flag inspections vs. foreign flag boardings) eight different RBR analyses were performed. These are summarized in Table 3.2. These analyses were performed for each of the 3 unit level designations (USCG, District, and MSO level) for a total of 48 risk-based ranking analyses of the Level III intervention strategies. The MSMS data was surveyed for the period 1991 through 1993. This represents the time frame over which the MSMS MINMOD data tables have been used.

Scope of MSMS Inspection/Boarding Records Included in the Analysis

The risk based ranking importance analyses were limited in scope to those inspection and boarding activities that were considered sufficiently comprehensive in scope so as to cover the full range of Level III intervention strategies. For U.S. flag vessel inspections the MSMS Marine Inspection Report Identification Table (IRIT) Inspection Of Vessels keywords were used to identify and tabulate the number of inspections performed by each unit. The inspection activities that were searched on were "Initial Inspection", "Certification Inspection", "Re-inspection", and "Hull Inspection". The MSMS Port Safety Resource Supplement Table

Table 3.2 Summary of Risk-Based Ranking Analyses For Each Unit Level Assessment

Vessel Flag	Bin Probability Measure	Casualty Consequence
U.S.	Relative Frequency	Deaths Injuries Property Loss Pollution
	Casualty Frequency	Deaths Injuries Property Loss Pollution
Foreign	Relative Frequency	Deaths Injuries Property Loss Pollution
	Casualty Frequency	Deaths Injuries Property Loss Pollution

(BRST) was used to search for and tabulate foreign flag vessels for each USCG unit. The boarding activities were identified from the BRST Activity Type keywords. The analysis of boarding activities was limited to "Annual Container", Annual Freight", "Annual Passenger","Pass Frgt", and "TANK VESS". These activities were defined as representative of comprehensive intervention activities the purpose of which are to inspect vessels for all aspects of marine safety. Other inspection and boarding activities were considered to be either too specific in nature or too peripheral in scope to permit a meaningful linking between casualty reports, nature of incident information (taken from the "Nature of Incident" keywords in the Marine Casualty Event Record Table [CEVT]), and the Level III intervention strategies.

3.2 Risk-Based Ranking Results

3.2.1 Data Aggregation and Relative Frequency and Casualty Frequency Estimates

The aggregation of the data as illustrated in Figure 3.1 for the USCG level analysis, Figure 3.2 for

the District level analysis, and Figure 3.3 for the MSO analysis, becomes progressively more detailed as the unit is defined more specifically. For each type of casualty consequence (deaths, injuries, property damage, and pollution) the USCG level analysis involves 6 bins, 3 for each category of flag (U.S. and foreign) as defined by the three service categories of vessels (freight, passenger, and tanker). At the next level of detail (District), 60 bins were defined by the 2 flag categories, 10 districts, and 3 vessel services. At the MSO level, 156 bins were defined by the 2 flag categories, 3 vessel services, and 52 MSOs. Each of these bin sets (6 for the top level [USCG], 60 for District, and 156 for MSO) was analyzed for 8 different risk based rankings as defined in Table 3.2. Because of the large amount of information generated by these analyses, only the results of the top-level assessment (USCG) will be discussed here. The District and MSO level results are documented in Appendix A, including data summary tables similar to Tables 3.3 and 3.4 (see Tables A.1.1, A.2.1, A.3.1, and A.4.1).

The summary of bin data used in the risk-based ranking calculations (number of inspections performed, number of casualties, relative frequency, casualty frequency, and consequence values) are in Table 3.3 for U.S. flag vessels and in Table 3.4 for foreign flag vessels. The results of the top-level USCG wide risk-based ranking analysis are summarized in Tables 3.5 and 3.6 (Relative Frequency weighting) and Tables 3.6 and 3.7 (Casualty Frequency weighting). The results in Tables 3.5 through 3.8 show the intervention strategy importance rankings normalized to the Level III intervention strategy most important to risk.

A comparison of the results for Relative Frequency Weighing and Casualty Frequency Weighing (Tables 3.5 and 3.7 for U.S. flag vessel, and Table 3.6 and 3.8 for foreign flag vessels) indicates that there is no significant difference between the importance rankings for either method of weighing casualty bin consequences, despite the fact that certain bins have significantly different Relative and Casualty frequencies, as shown in the **Relative Frequency** and **Casualty Frequency** columns of Tables 3.3 and 3.4. The results of the risk-based ranking are not informative about contributors to specific types of consequences (i.e., deaths, injuries, property damage, and pollution). The Relative Frequency Weighing results in Tables 3.5 and 3.6 illustrate very minor variations in the importance of the various inspection activities based on type of casualties. The Casualty Frequency Weighing results yielded exactly the same importance measures for the inspection activities regardless of the type of consequence. Thus, the results in Tables 3.7 and 3.8 are not differentiated on the basis of consequences.

The lack of distinguishing information on the basis of consequence type is attributable to the nature of the mapping of casualty causal data to the Level III Intervention Strategies. This mapping process is introduced in the discussion of the methodology in Section 2.1.2 and the application of this process to the MSMS MINMOD CEVT table is illustrated in Appendix C. Ideally, a detailed mapping for each type of consequence would be performed to develop specific measurements of the importance of Level III Strategies for each type of consequence. However, for this analysis a single aggregate mapping was performed. Casualty causal data was mapped only once to each bin, and the mapping was based on whether or not specific causal data was relevant to the casualties in each bin. No distinction was made to delineate causal data on the basis of consequence type. The results are heavily influenced by the limited detail of the linking of casualty cause keywords of the MSMS MINMOD CEVT table and the Level III Intervention Strategies.

Table 3.3 Risk-Based Ranking Bin Data Summary - USCG Wide Aggregation, U.S. Flag

Service	Inspections	Casualties	Relative Frequency	Casualty Frequency	Casualty Frequency Standard Deviation	Consequences			
						Deaths	Injuries	Property Losses	Pollution Releases (gal.)
FREIGHTER	1924	985	0.5072	0.51195	0.0114	11	324	$27,708,561	47,676
PASSENGER	4685	337	0.1735	0.07193	0.0038	2	50	$2,863,371	1259
TANKER	1204	620	0.3193	0.51495	0.0144	4	167	$6,554,482	8599
Total	7813	1942	1.0	-	-	17	541	$37,126,414	57,534

Table 3.4 Risk-Based Ranking Bin Data Summary - USCG Wide Aggregation, Foreign Flag

Service	Boardings	Casualties	Relative Frequency	Casualty Frequency	Casualty Frequency Standard Deviation	Consequences			
						Deaths	Injuries	Property Losses	Pollution Releases (gal.)
FREIGHTER	17,916	870	0.67	0.05	0.0016	9	23	$23,959,892	440,208
PASSENGER	99	62	0.05	0.63	0.049	1	28	$13,020,000	300
TANKER	2557	363	0.28	0.14	0.0069	3	15	$2,679,945	161,471
Total	20,572	1295	1.0	-	-	13	66	$39,659,837	601,979

Table 3.5 Risk-Based Ranking - USCG Wide Aggregation, US Flag, Relative Frequency Weighting

Service	Consequence	Level III Intervention Strategies									
		Cargo/ Poll.	Steering/ Nav.	Documents/ Paperwork	Drills/ Human Factors	Auxiliary Sys.	Power Plant	Fire Prevention	Hull	Lifesaving	Other
Freight	Deaths	0.29	0.50	0.00	1.00	0.00	0.08	0.04	0.10	0.00	0.08
	Injuries	0.30	0.48	0.00	1.00	0.00	0.08	0.04	0.13	0.00	0.07
	Property	0.37	0.57	0.00	1.00	0.00	0.11	0.05	0.14	0.00	0.07
	Pollution	0.22	0.43	0.00	1.00	0.00	0.05	0.03	0.08	0.00	0.07
Passenger	Deaths	0.09	1.00	0.00	0.42	0.00	0.05	0.07	0.07	0.00	0.07
	Injuries	0.10	1.00	0.00	0.38	0.00	0.16	0.08	0.10	0.00	0.03
	Property	0.10	1.00	0.00	0.36	0.00	0.16	0.08	0.07	0.00	0.03
	Pollution	0.17	1.00	0.00	0.36	0.00	0.12	0.06	0.03	0.00	0.06
Tanker	Deaths	0.51	0.67	0.00	1.00	0.00	0.05	0.01	0.18	0.00	0.14
	Injuries	0.55	0.71	0.00	1.00	0.00	0.10	0.03	0.21	0.00	0.08
	Property	0.59	0.99	0.00	1.00	0.00	0.10	0.03	0.22	0.00	0.09
	Pollution	0.80	0.74	0.00	1.00	0.00	0.13	0.05	0.31	0.00	0.08

Table 3.6 Risk-Based Ranking - USCG Wide Aggregation, Foreign Flag, Relative Frequency Weighting

Service	Consequence	Level III Intervention Strategies									
		Cargo/ Poll.	Steering/ Nav.	Documents/ Paperwork	Drills Human Factors	Auxiliary Sys.	Power Plant	Fire	Hull	Lifesaving	Other
Freight	Deaths	1.00	0.84	0.00	0.11	0.00	0.08	0.02	0.06	0.00	0.07
	Injuries	0.94	1.00	0.00	0.15	0.00	0.10	0.02	0.06	0.00	0.08
	Property	1.00	0.87	0.00	0.13	0.00	0.09	0.02	0.07	0.00	0.06
	Pollution	1.00	0.88	0.00	0.10	0.00	0.10	0.01	0.05	0.00	0.07
Passenger	Deaths	0.00	0.14	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	Injuries	0.05	0.16	0.00	1.00	0.00	0.01	0.02	0.00	0.00	0.00
	Property	0.00	0.14	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	Pollution	1.00	0.29	0.00	0.46	0.00	0.14	0.29	0.00	0.00	0.00
Tanker	Deaths	1.00	0.76	0.00	0.14	0.00	0.05	0.06	0.04	0.00	0.06
	Injuries	1.00	0.92	0.00	0.18	0.00	0.04	0.11	0.08	0.00	0.08
	Property	1.00	0.91	0.00	0.17	0.00	0.05	0.12	0.07	0.00	0.08
	Pollution	1.00	0.68	0.00	0.11	0.00	0.07	0.04	0.03	0.00	0.03

Table 3.7 Risk-Based Ranking - USCG Wide Aggregation, U.S. Flag, Casualty Frequency Weighting

Service	Level III Intervention Strategy									
	Cargo/ Poll.	Steering/ Nav.	Documents/ Paperwork	Drills/ Human Factors	Auxiliary Sys.	Power Plant	Fire Prevention	Hull	Lifesaving	Other
Freight	0.36	0.58	0.00	1.00	0.00	0.12	0.05	0.15	0.00	0.07
Passenger	0.14	1.00	0.00	0.29	0.00	0.15	0.07	0.10	0.00	0.04
Tanker	0.63	0.72	0.00	1.00	0.00	0.15	0.04	0.22	0.00	0.08

Table 3.8 Risk-Based Ranking - USCG Wide Aggregation, Foreign Flag, Casualty Frequency Weighting

Service	Level III Intervention Strategies									
	Cargo/ Poll.	Steering/ Nav.	Documents/ Paperwork	Drills/ Human Factors	Auxiliary Sys.	Power Plant	Fire Prevention	Hull	Lifesaving	Other
Freight	1.00	0.89	0.00	0.13	0.00	0.08	0.03	0.08	0.00	0.06
Passenger	0.33	0.21	0.00	1.00	0.00	0.04	0.08	0.00	0.00	0.00
Tanker	1.00	0.71	0.00	0.13	0.00	0.04	0.06	0.04	0.00	0.05

3.2.2 U.S. Flag Risk Based Rankings - USCG Wide Data Aggregation

The results of the U. S. Flag risk-based ranking analysis indicate that Drills/Human Factors and the Steering/Navigation inspection intervention strategies are the two most dominate contributors, regardless of the service of vessel. The Cargo Handling/Pollution Control intervention activity is also dominant for freighters and tankers, but not for passenger vessels. Other intervention activities that have relatively small risk rankings are Power Plant, Fire Fighting/Prevention, Hull, and "Other" (the "Other" category was defined to account for CEVT records for which no casualty cause keywords mapped into any of the Level III Intervention Activities). There were no casualty keywords in CEVT that were relevant to the Documents/Paperwork, Auxiliary Systems, and Life Saving intervention strategies (see Appendix C). The ranking of the dominant contributors to risk are similar regardless of the casualty consequence, although there are some differences in ranking based on the consequences.

For example, based on the Relative Frequency weighted results in Table 3.5, all risks (deaths, injuries, property loss, and pollution) for both freight and tanker services are most dominated by Drills/Human Factors related causes. Steering and Navigation causes are the next most dominant for these services, ranging from 43% to 57% as important as Drills/Human Factors for Freight and ranging from 67% to 99% as important for Tankers (the range is established by variations in importance for different risks). For passenger vessels the ranking is dominated by Steering and Navigation causes for all risks, followed by Drills/Human Factors causes (ranging from 36% to 42% as important as Steering and Navigation). The ranking results for the Casualty Frequency weighted results in Table 3.6 are very similar.

3.2.3 Foreign Flag Risk Based Rankings - USCG Wide Data Aggregation

The risk-based ranking results for foreign flag vessels are essentially the same for the Relative Frequency weighted and Casualty weighted analyses. Only minor shifts in rankings are observed. For example, injury risk for freighters Cargo Handling/Pollution Control causes is most dominant for Casualty Frequency weighting with Steering/Navigation causes 89% as important. For Relative Frequency importance Cargo Handling/Pollution Control is the second most important cause for injury risk for freighters, 94% as important as Steering/Navigation.

3.2.4 Data Issues and Uncertainties

3.2.4.1 Statistical Uncertainty of the Casualty Frequency Estimations

Several data issues must be considered when evaluating the significance of the risk-based ranking results. One issue is the uncertainty associated with the Casualty Frequency for each bin. The degree

of uncertainty for this term can be measured by calculating its standard deviation. Using the following approximation for standard deviation for a binomial random variable:

$$(p^*(1-p)/n)^{1/2}$$

where:

$p \equiv$ Casualty Frequency, and
$n \equiv$ number of inspections.

The results of these calculations are shown in Tables 3.3 and 3.4 (similar calculations for District and MSO level data aggregation are in Appendix A). The results show that as the number of inspections increases, the standard deviation decreases, establishing a greater confidence in the statistical validity of the casualty frequency estimates.

3.2.4.2 Uncertainty Regarding Validity of Inspection and Casualty Data

The validity of the risk-based ranking analysis is highly dependant on the quality of the data incorporated into the analyses. The most noticeable issue encountered in the data queries of the MSMS MINMOD database was inconsistent logging of casualty information. For both the Relative Frequency and Casualty Frequency bin probability measures, the number of casualties "attributable" to each bin was calculated by linking casualty reports in CIRT to the unit of the last relevant inspection in IRIT. The RBR importance ranking used casualty cause keywords in CEVT to link the casualty causes to the Level III Intervention Strategies. However, casualty data was not consistently entered for all casualty reports. Of the 1942 casualties identified in this study that involved relevant U.S. flag vessels, 492 (25%) of these reports had no record entered in to the CEVT table. For foreign flag vessels, 358 out of 1295 identified casualties (28%) had no CEVT record. These data were included in the estimation of the bin probability measures because they reflect real information on the rate of casualty occurrence, but they could not be used in developing the risk-based ranking to identify the importance of the Level III Intervention Strategies to risk.

Another data uncertainty issue is the validity of the data used in the risk-based ranking analysis, specifically regarding the accuracy of the number of inspections and casualties assigned to each bin. An example that clearly indicates a problem regarding identifying which inspections and casualties belong to each bin is illustrated by the data results for the MSO level bin **MSO-Honolulu-Passenger**. A total of 19 relevant boardings on foreign flag passenger vessels were identified for this bin, but a total of 28 casualties involving foreign flag passenger vessels were "attributed" to this bin as well, for a casualty frequency of 1.5 casualties/inspection. This suggests that a problem exist with either the data entered into the database or the query process is missing a subtlety involving the relationship of the data links between tables. The results for this bin raise an obvious flag regarding data quality or the complexity of the querying process. The data for Honolulu is obviously flawed, however, the accuracy of data for other bins should also be scrutinized and verified before the risk-based ranking results can be accepted at face value.

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4.0 Econometric Models and Estimates

In this section we present estimates from the econometric models. This together with the RBR results form the basis for measures of effectiveness (MOEs) at all three levels of the USCG inspection and boarding program. These results are also the basis for policy recommendations and the decision support system (DSS) methodology we develop. We also offer observations and recommendations pertaining to data quality, data deficiency, and data strengths, from the perspective of users of the MSMS database.

4.1 Overview

We present the results in two parts - one set of estimates for the Marine Inspection Program for U.S. flag deep-draft vessels, and another for the Port Safety Program covering Foreign flag deep-draft vessels. We do this for two reasons. Firstly, the Level I, II, and III activities described in Section 1 naturally segment into these two flag-separated groups. Secondly, and perhaps more importantly, information pertaining to U.S. flag vessels is more "complete" or "more certain" than for Foreign flag vessels. We will make this distinction clear in the discussion of the results, but the upshot is that we obtain quite different inferences for U.S. flag vessels than for Foreign flag vessels.

The econometric analysis is designed to answer the following question: How effective is the USCG inspection and boarding program in controlling or reducing Personnel casualties and Pollution casualties ? A second and possibly more important question that the analysis helps to answer is the following: How can the USCG reprogram its activities to become more effective in reducing Personnel and Pollution casualties ?

Two classes of econometric models are employed to provide quantitative answers to these questions. Poisson models are used to infer the effectiveness of USCG resources devoted to the inspection and boarding program in reducing or controlling the *number* of Personnel casualties and Pollution casualties. The Poisson distribution has been usefully applied to problems such as marine accidents, number of successful oil explorations, number of product failures, to name a few examples. A Poisson model is appropriate for a discrete random variable where the value of the random variable is generally small, which fairly represents Personnel and Pollution Casualties. Duration models are used to infer the effectiveness of USCG resources in *increasing* the *time between such casualties.* These are variations of time-to-failure models which have been extensively used in engineering. Poisson models provide appropriate Level I and Level III MOEs, and duration models provide appropriate MOEs for Level II activities. In addition to Poisson models, we have experimented with other nonlinear models such as Probit and Logit models[3] but their results are not qualitatively different from the Poisson results, and have not been reported.

The actual models estimated are based on the theory provided in Section 2.0. The econometric

[3] For descriptions and technical details of these and other models see e.g. Greene, William, 1993, Econometric Analysis, New York: Macmillan.

models are based on cross-sectional data across deep-draft vessels. The estimating equations for both the Poisson and Duration models differ in the measurement of the dependent or left-hand-side (lhs) variables: for the Poisson model the lhs variable is the number of occurrences of casualties and for the Duration models the lhs variable is time-to-casualty. These different measurements necessitate different estimation techniques, which are detailed subsequently. Both the Poisson and Duration models have identical explanatory or right-hand-side (rhs) variables. Variations in the lhs variable are explained by the number of resource hours expended by the USCG inspection/boarding program, and a set of control variables that measure vessel characteristics, such as vessel age, and gross tonnage. The estimated coefficients on the resource hour variables *are* MOEs from the econometric models. They quantify the response of the dependent variable, namely occurrence of or duration between casualties, to changes in resource hours, and therefore measure the effectiveness of USCG activities in controlling or reducing Personnel and Pollution casualties.

4.2 Data Construction

4.2.1 Data Construction for the Poisson Model

For the Poisson model the data are arranged by vessel. 951 deep draft U.S. flag vessels, and 10907 deep draft Foreign flag vessels are included in the analyses. Table **4.0** describes the variables used in the econometric analysis. For each U.S. flag vessel, resource hours devoted to Marine Inspection hull activities (HULL_HR), machinery activities (MACH_HR), and administrative activities (ADMIN_HR) between 1989 and 1993 are computed from table CRST. Vessel characteristics such as gross tonnage (REG_GT), and vessel age (AGE) are computed from table VIDT. For each U.S. flag vessel, the number of Personnel casualties (DEATHS, MISSING, INJURED) and Pollution casualties (POLLOCCS) are computed from the MINMOD tables, particularly CIRT, between 1991 and 1993. For each Foreign flag vessel, resource hours devoted to Port Safety activities, mainly annual examinations, (REG_HR, RES_HR, ADMIN_HR) between 1989 and 1993 are computed from table BRST. Vessel characteristics and casualty data are constructed in the same manner as for U.S. flag vessels. [4]

Essentially each vessel is considered an independent "experiment". So we have 951 experiments on U.S. flag vessels (Marine Inspection, or MI, cases) and 10907 experiments on Foreign flag vessels (Port Safety, or PS cases). The Poisson model is estimated separately for the MI and PS experiments. From the MI experiments we infer from the estimated coefficients on the resource hours whether MI activity has been effective in reducing or controlling Personnel and Pollution casualties on U.S. flag deep-draft vessels. For Personnel casualties, separate analyses are provided for (i) number of deaths

[4] Other data that have been constructed for both U.S. and Foreign flag vessels and employed in the simultaneous models are as follows: number of deficiencies from an inspection/boarding (from tables IRIT, AVST), number of COI inspections, number of Reinspections, number of Hull Exams, number of Administrative inspections, number of Initial inspections, number of Construction inspections, number of Defective inspections, number of Other inspections (all from IRIT), number of Annual Freight exams, number of Annual Passenger Exams, number of Annual Tank Exams (all from BRST).

and missing (D&M) and (ii) number injured (INJURED). PS cases are similarly analyzed.

4.2.2 Data Construction for the Duration Model

i. Marine Inspection Cases:

For MI cases, three types of inspections are considered: COI, Reinspection, and Hull Exam. These are in fact Level II.A type activities. The indicators in table IRIT are used to select these inspections. The data is arranged not by vessel as for the Poisson model, but by vessel inspection. The experimental unit is not a vessel, but the *inspection* of a vessel. Hence a vessel may appear more than once in a duration data set if it underwent two inspections during 1989-1993. The lhs variable is duration to casualty from the last inspection. The following example makes clear the construction of this duration measure. Suppose vessel A undergoes inspection of type I1 on date ID1, and then inspection of type I2 on date ID2, these are counted as two different experiments. The duration from the date of inspection, Iritdate (from table IRIT), to date of casualty, Cirtdate (from table CIRT), is the lhs variable in the Duration model. Suppose vessel A experienced a casualty (say, pollution casualty) on date CD1, then corresponding to the two inspections we get two duration data (CD1-ID1) and (CD1-ID2), respectively. All inspections since 1/91 are considered since casualties beginning 03/91 are in MINMOD (where CIRT resides). If a vessel has no casualties till the period 12/93 (the last date in the database we consider), then the "duration" associated with inspections on that vessel are the days between the inspection date and 1/1/95. This rather ad hoc assumption needs to be made since most Duration models are confronted with precisely this problem of assigning durations to events that have not yet been completed. A long duration is therefore indicative of a "failure that has a weak link with an inspection". This is the correct interpretation of duration and applies not only to non-casualties, but to casualties that happen long after an inspection. Suppose vessel A underwent inspection of type I1 on 1/1/92. It underwent the same inspection again in 1/1/93. Suppose it met with a casualty on 1/3/93. The duration associated with its 1993 inspection is then 60 days, while the duration associated with its 1992 inspection is 425 (365+60) days. The latter indicates a weak link, if any, with the 1992 inspection but a strong link with the 1993 inspection. This is consistent with the treatment of non-casualties as explained above. A possible improvement, which requires better information concerns the linkage between an inspection and a casualty. But this information is unavailable from the MSMS database.

The rhs resource variables are computed similarly as for the Poisson model, except that hours spent on each Level II activity (rather than on a vessel) are computed from CRST and IRIT.

ii. Port Safety Cases:

The analysis for PS cases is the same except for the following differences:
(a) the resource hours data is constructed from BRST, BRIT, and AVST (CRST and IRIT are used for MI cases), and
(b) three types of examinations are considered: Annual Foreign Freight Exams, Annual Foreign Tank Exam, Annual Foreign Passenger Exam. These are in fact the Level II.B type activities. Whereas for Level II.A activities (MI cases) the selection is based on indicators in IRIT, for Level II.B activities (PS Cases), a mapping from BRST inspection types to Level II.B activities is used. This mapping is provided in the appendix.

4.3 Statistical and Estimation Details

4.3.1 Poisson Model:

Used to analyze count data, e.g. number of accidents, number of strike days, number of customer complaints, number of oil wells, number of doctor visits.

A Poisson model is used to analyze number of deaths, injuries in casualties involving personnel, and number of pollution incidents in casualties involving pollution.

$$Prob(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, \qquad y_i = 0,1,2,...$$

In a Poisson distribution there is one parameter, λ. A Poisson r.v. has the has the property that its mean (and variance) are both equal to λ.

$$E(y_i) = \lambda_i$$

Here λ is subscripted by i to show that the expectation of y varies across observations i. It is hypothesized that λ_i is related to other characteristics of i, measured by the vector $\boldsymbol{x}_i$, as follows:

$$\ln \lambda_i = \beta' \boldsymbol{x}_i$$

The Poisson model is applied to a data set that comprises of inspections and casualties on 951 deep draft vessels for which such data is available. A unique vessel appears once in the data set and is indexed by i. Hull, machinery, and administrative hours between 1989 and 1993 together with the variables vessel age, and gross tonnage make up the vector of *explanatory variables* $\boldsymbol{x}_i$.

The *dependent variable* is the number of personnel casualties for each vessel since 1991. For example the range for personnel deaths is between 0 and 7.

It is clear that the response of the expected value of the dependent variable to a change in an independent variable, say, x_i is given by

$$\frac{\partial E(y_i \mid x_i)}{\partial x_i} = \lambda_i \beta$$

The parameter vector β is estimated by maximum likelihood, and the responses are calculable from the last equation. The responses on the variables measuring inspection hours can thus estimate, for example, "the reduction in the expected number of personnel casualties with an increase of one hour of an inspection".

4.3.2 Duration Model: [5]

We use the form of the Duration model used in King, Alt, Burns, and Laver (1989).[6]
Let y_i, $i=1,...,n$ take on any non-negative real number representing a duration. Often y_i is measured as an integer (as we do), such as the number of days or months. Even so, if the dependent variable is a measure of time, duration models, and not event count models (like Poisson), are called for. Let y_i be distributed exponentially with mean μ_i. Then we can write the density of y_i as

$$f(y_i) = \frac{1}{\mu_i} e^{-\frac{y_i}{\mu_i}}, \quad \mu_i > 0, \ \infty > y_i \geq 0$$

The exponential density is often useful for modelling the length of life of electronic components. Suppose that the component is such that the length of time it has already operated does not affect the component's chance of operating at least b additional time units. That is, the probability that

[5] For details on Duration models see Kalbfleisch J. D. and R. L. Prentice, 1980, The Statistical Analysis of Failure Time Data. New York: Wiley. For duration models in econometrics see N. Keifer, 1988, "Economic Duration Data and Hazard Functions", Journal of Economic Literature, 26, pp. 646-679.

[6] King, Gary, James Alt, Nancy Burns, Michael Laver, 1989, "A Unified Model of Cabinet Duration in Parliamentary Democracies", mimeograph, Kennedy School of Government, Harvard University.

the component operates for more than $a+b$ time units, given that it has already operated for at least a time units, is the same as the probability that a new component will operate at least b time units if the new component is put into service at tim 0. We feel that this "memoryless" property of this distribution is an attractive feature and appropriate for modelling time to casualty of U.S. flag and Foreign flag vessels.

If we model μ_i, which is a positive number, as a log-linear function of the explanatory variable x_i,

$$E(y_i) \equiv \mu_i = \exp(x_i \beta)$$

then we get an exponential regression model. Estimation is by maximum likelihood. Elements of the vector β measure the percent response of duration-to-casualty to a change in the corresponding rhs variable. For example, an estimate of the vector β directly provides an answer to the question "by what percent will the duration to a casualty increase if we increase the number of hours devoted to hull-related activity (i.e. HULL_HR) by 1000 hours".

4.4 U.S. Flag Vessels: Econometric Results and Level I, II, and III MOEs

4.4.1 Data Description: Marine Inspection of U.S. Flag Deep-Draft Vessels

Figures 4.0.1-4.0.3 display number of Personnel and Pollution casualties by vessel service for U.S. flag deep-draft vessels. Casualties are constructed from the MINMOD tables in the MSMS database, which is a relatively new component of the database and includes casualties beginning 1991. Freight ships account for 75% of all Dead and Missing (D&M) casualties, and about 60% of Injured casualties. Pollution casualties are equally shared by Freight and Tank ships. Figure 4.1.1 shows the breakdown of our sample by service. Of 951 deep-draft U.S flag vessels, 53% are Freight ships, 32% are Tank ships, and 15% are Passenger ships. Hours devoted to Marine Inspections between 1989 and 1993 are displayed in aggregate in Figure 4.1.2 and by service in Figure 4.1.3. The three main types of hours - Hull hours, Machinery hours, and Administrative hours - are included in the empirical analysis. Nearly 1.2 million hours were devoted to Hull activities, 800,000 hours to Machinery activities, and 1.15 million hours to Administrative hours (hours that did not involve actual inspections). This works out to approximately 250 Hull hours, 167 Machinery hours, and 240 Administrative hours per deep-draft vessel per year. Note that these numbers include activities such as Construction and Initial Inspections which are very resource-intensive and inflate the averages. Typically about 100-150 Hull hours, 50-100 Machinery hours, and 100-150 Administrative hours are expended annually per deep-draft U.S. flag vessel. Vessel characteristics such as gross tonnage and age are displayed in Figures 4.1.4 and 4.1.5. Passenger vessels are the smallest of deep-draft U.S. flag vessels in terms of gross tonnage (they are dwarfed in size by Foreign flag Passenger vessels). The U.S. fleet of deep draft vessels is both smaller (in number of vessels as well as size of vessels) and older than the world's fleet, perhaps reflecting the fact that it is more costly to own and operate deep-draft vessels in the regulatory environment that exists in the U.S. that prevent economies of scale that are essential to success in this industry.

Average duration to Personnel casualty after each Type II.A activity is displayed in Figures 4.1.6-4.1.8. Conditional on the fact that there is a casualty, on the average it occurs about 250 to 300 days from an inspection, depending on service. This is indicated by the bar labelled "Dur-cas". Where there is no casualty, we compute the "duration" as the number of days between that inspection and 1/1/1995. This results in an average of about 950 to 1000 days (the bar labelled "Dur-nocas") for inspections that do not see a casualty at all.
The corresponding durations to Pollution casualty that appear in Tables 4.1.9-4.1.11 show that the average duration to a casualty is about 300 to 400 days.

Figure 4.0.1

MI Cases:Number DEAD & MISSING, 1991-93

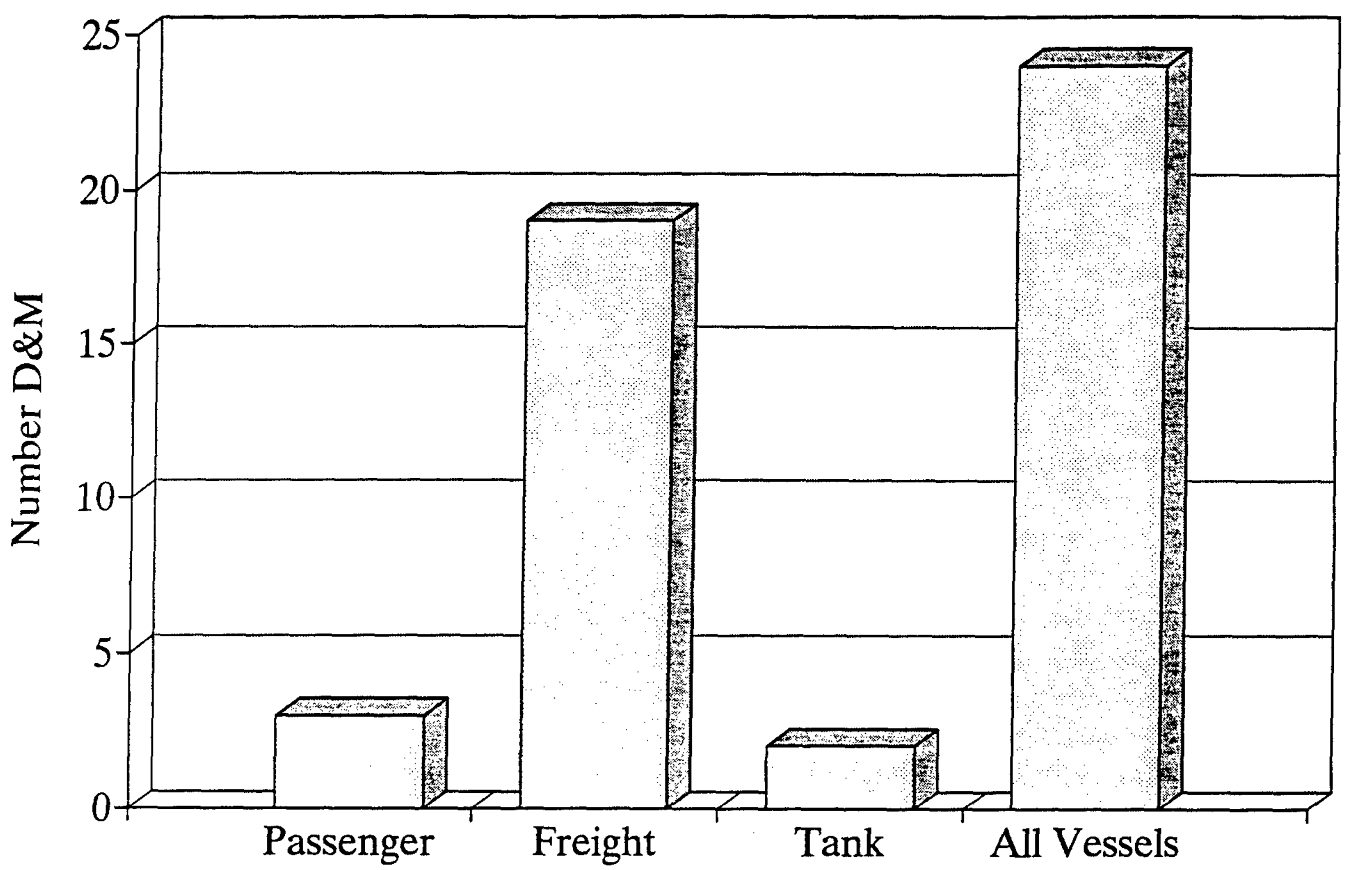


Figure 4.0.2
MI Cases: Number INJURED, 1991-1993

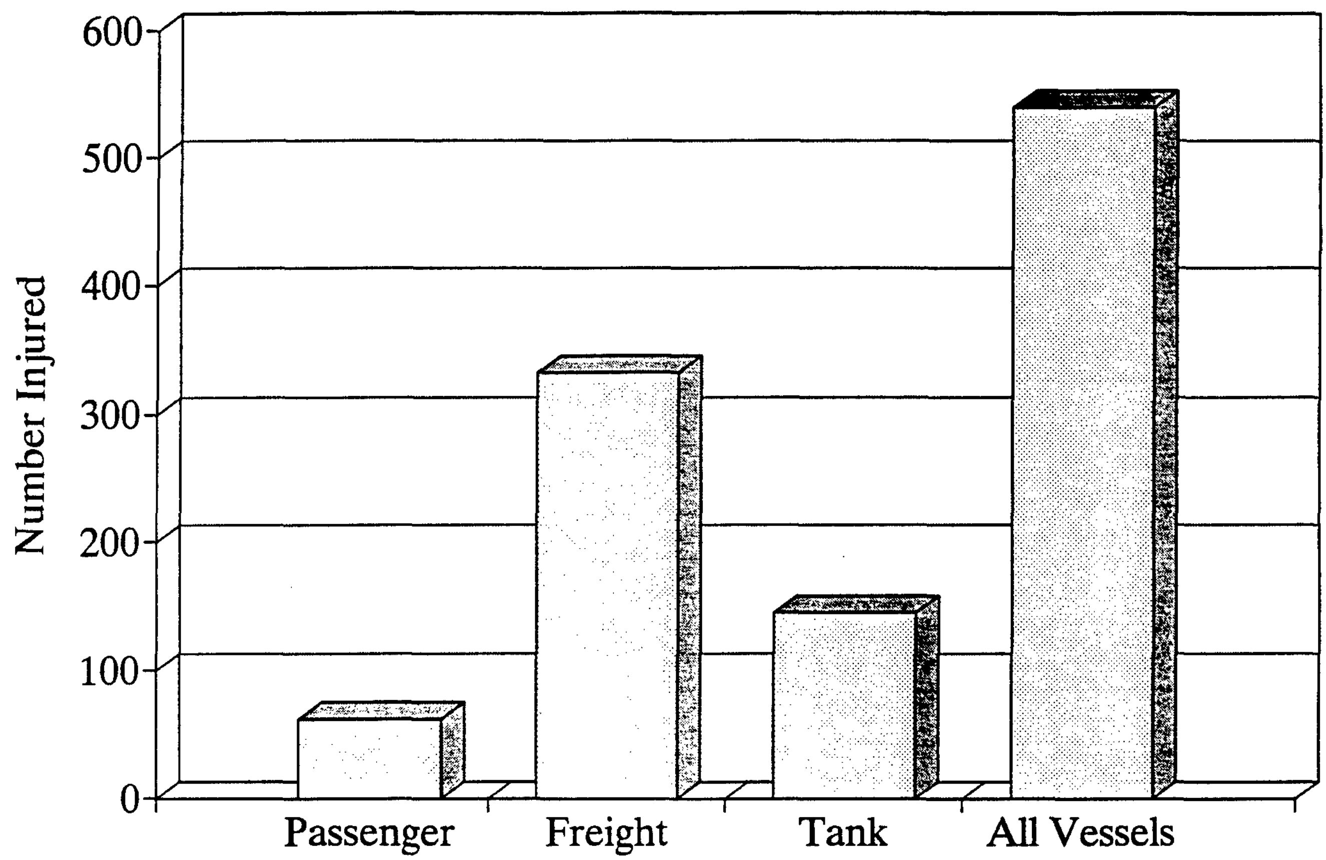


Figure 4.0.3
MI Cases: POLLUTION Casualties, 1991-93

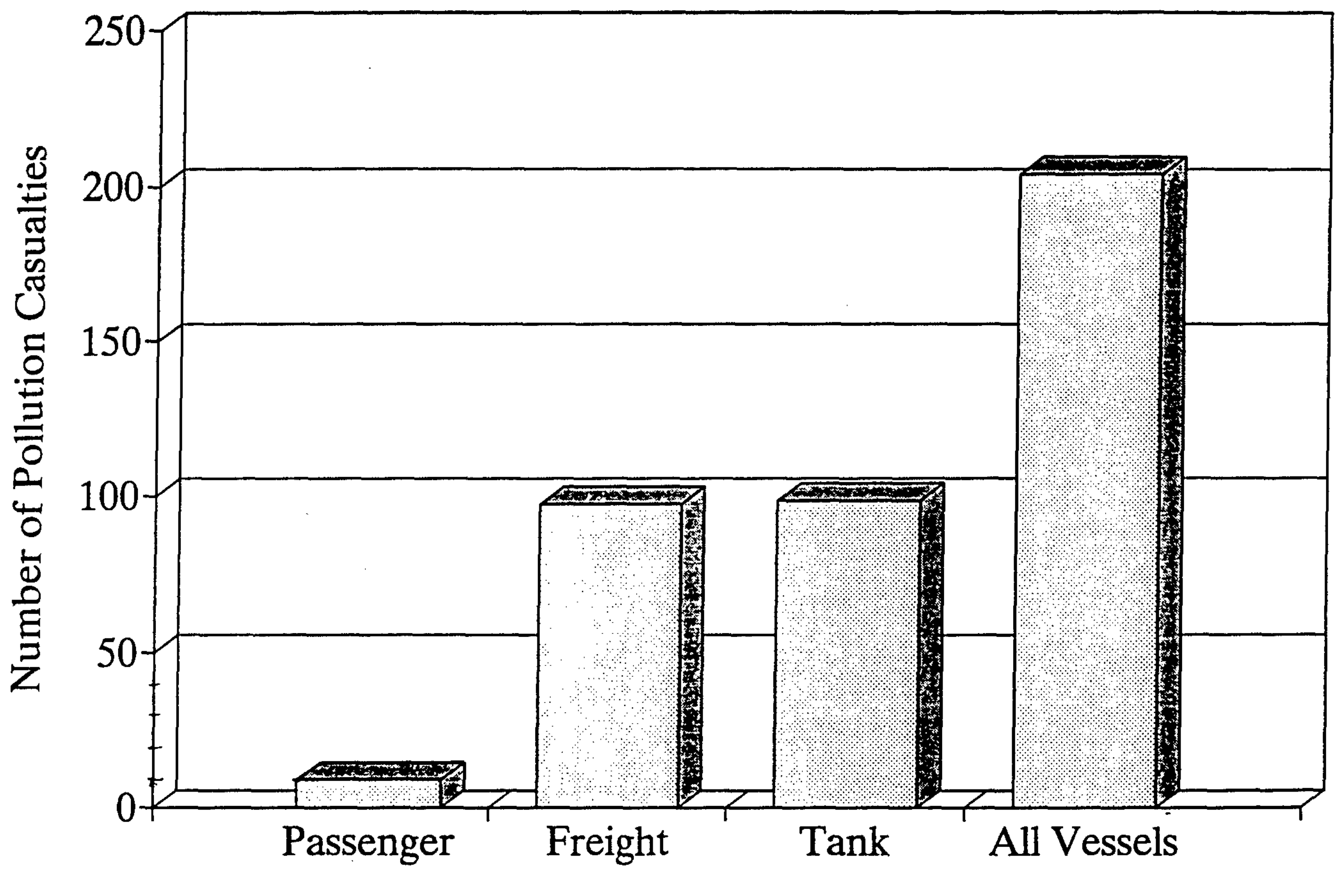
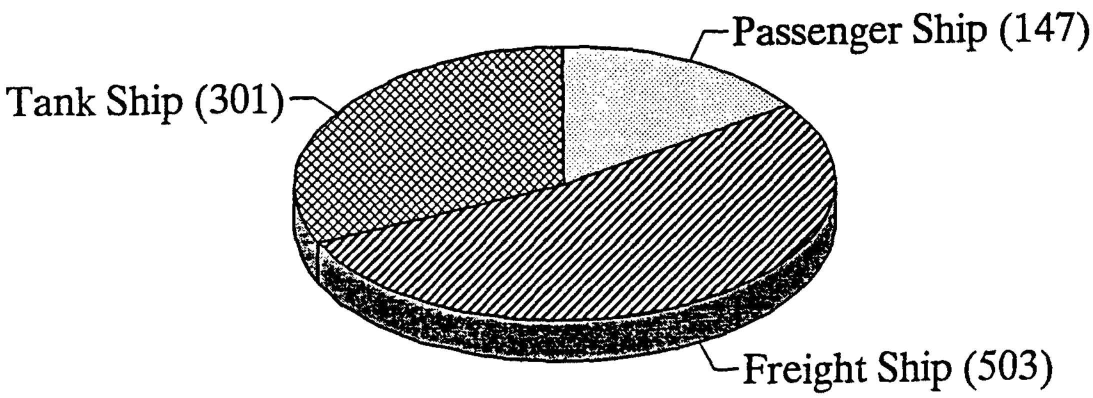


Figure 4.1.1
Deep Draft Vessels, MI Cases



Total = 951

Figure 4.1.2

Total Inspection Hours, MI Cases, 1989-1993

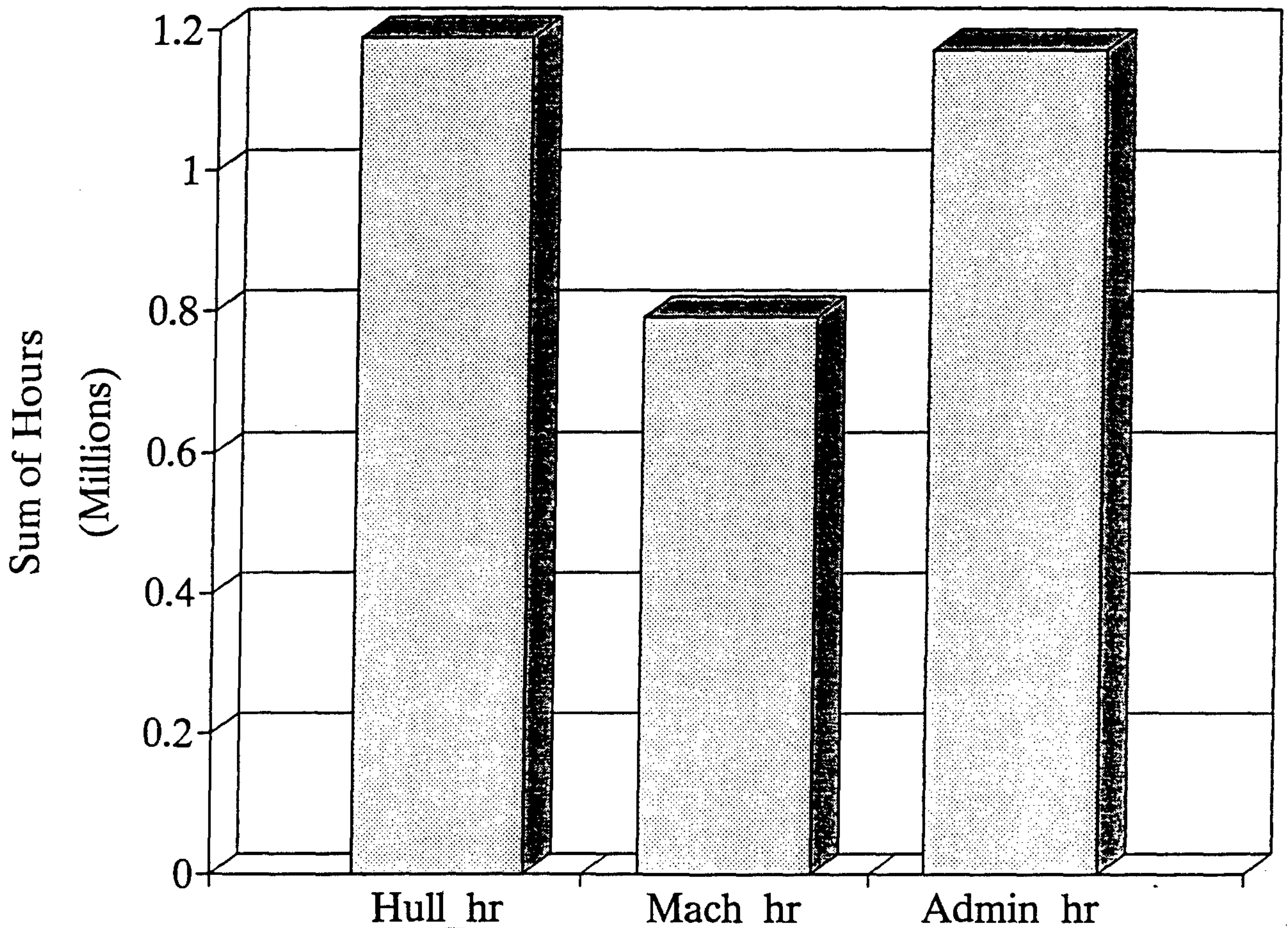


Figure 4.1.3

Inspection Hours by Service, MI Cases, 1989-1993

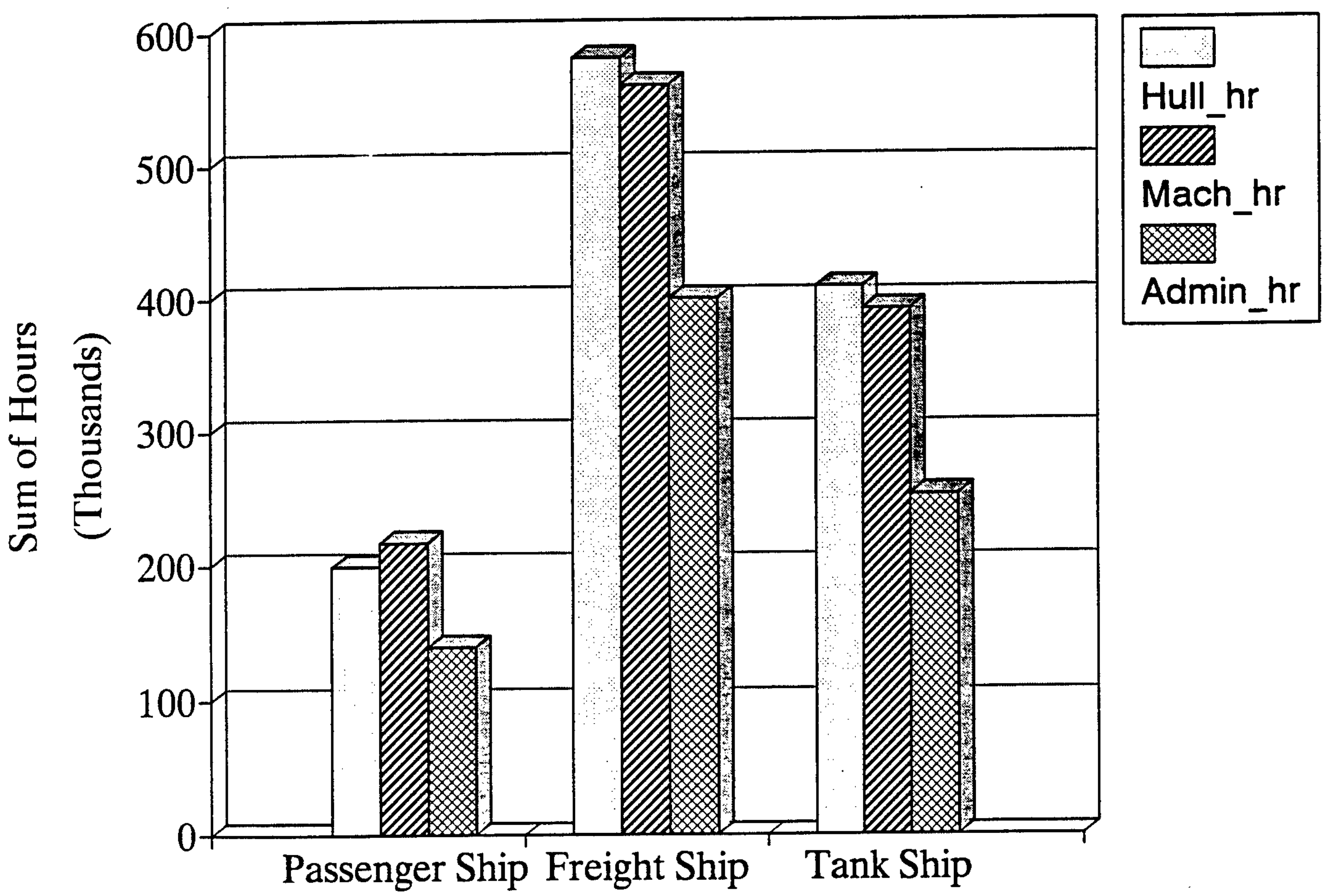


Figure 4.1.4

Average Gross Tonnage by Service, U.S. Flag

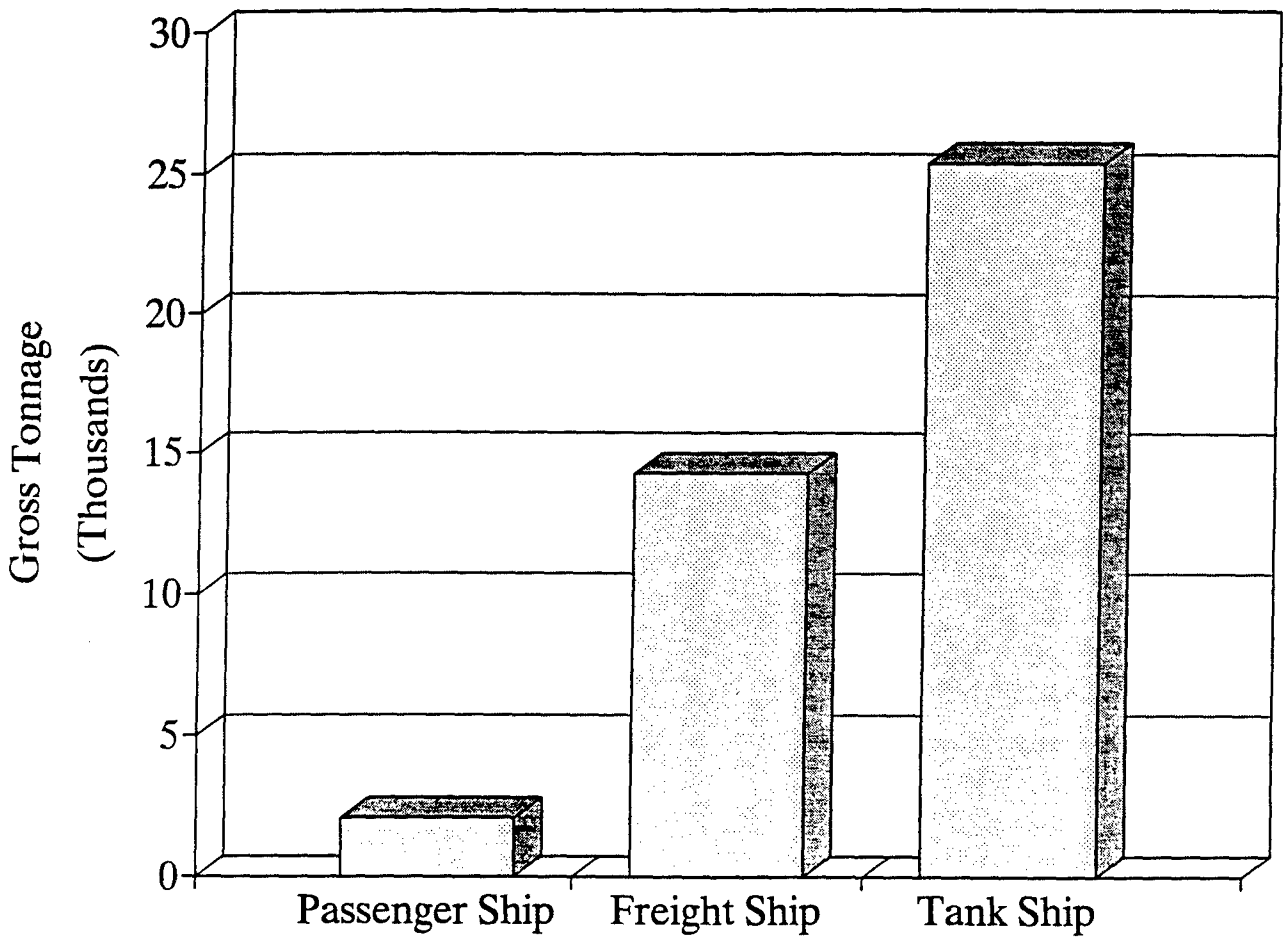


Figure 4.1.5
Average Age of Vessel, U.S. Flag

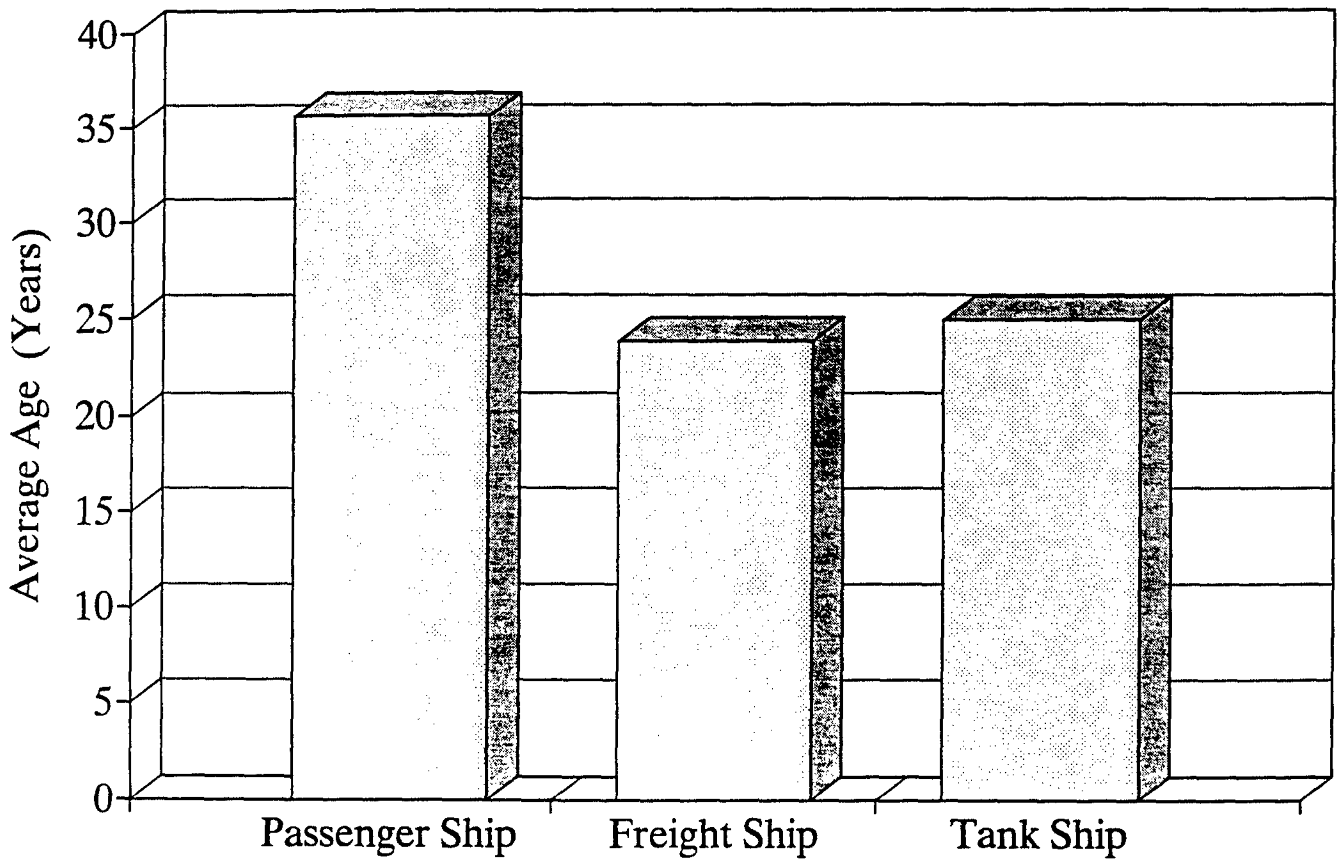


Figure 4.1.6

Average Duration to Personnel Casualty

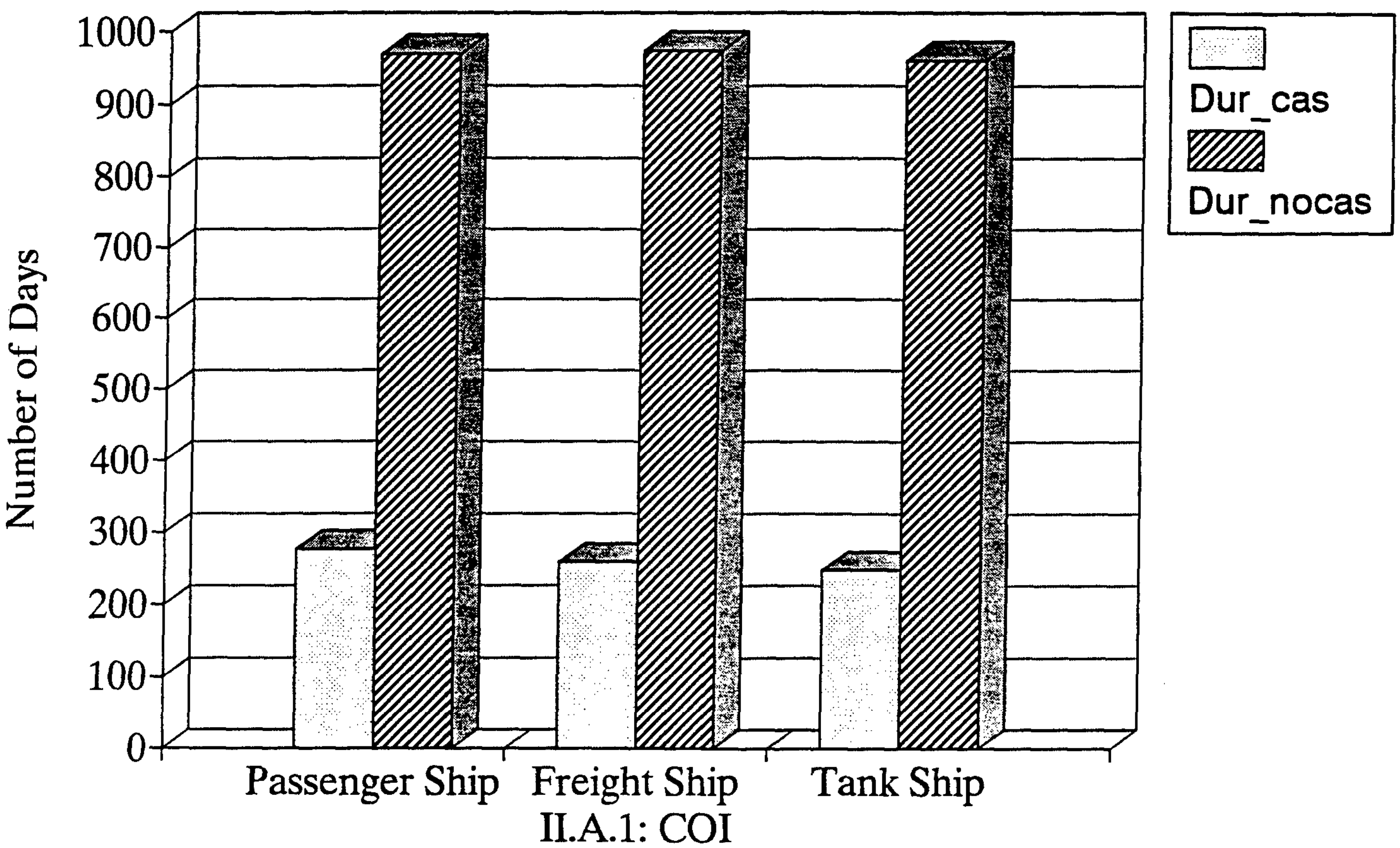
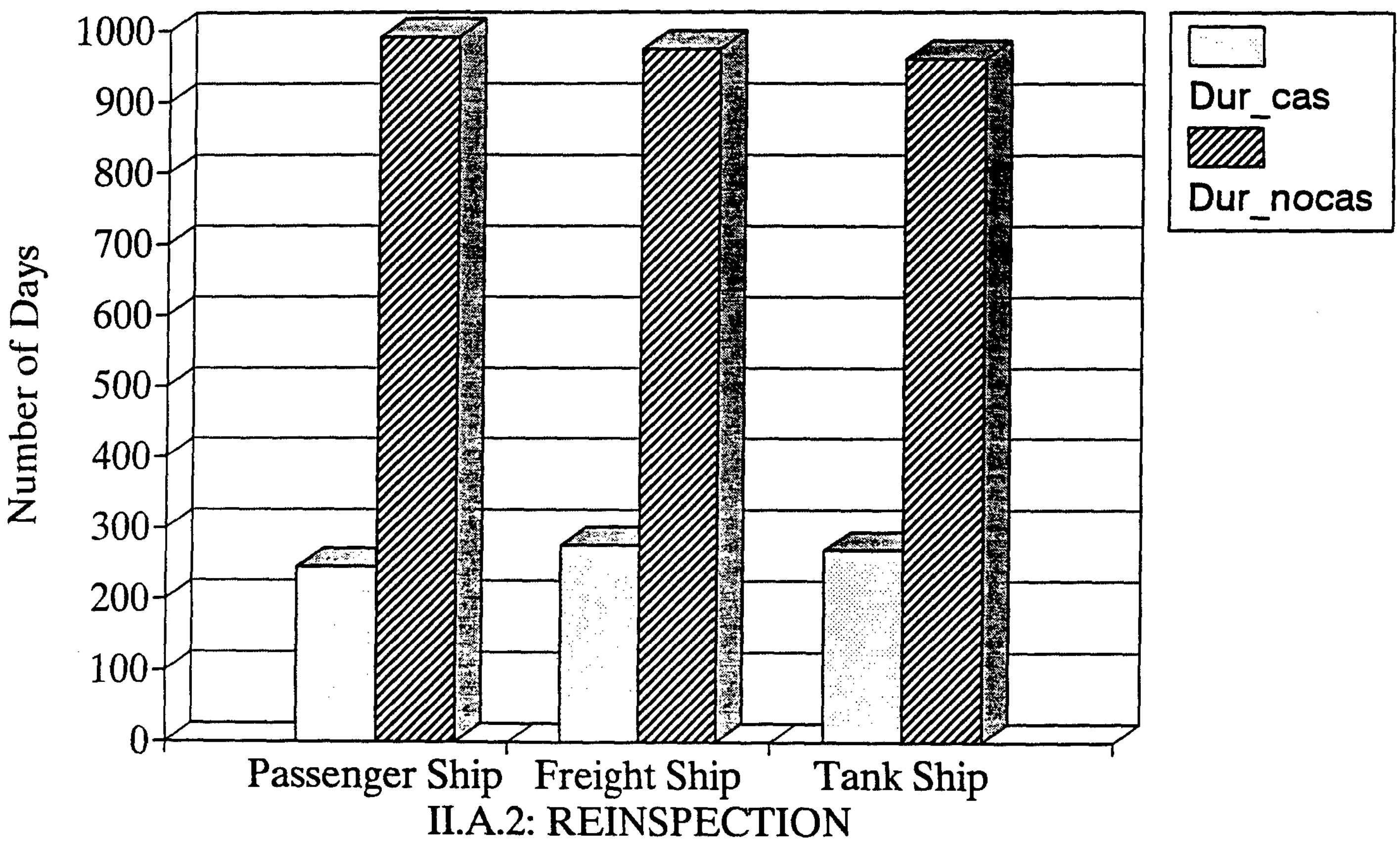


Figure 4.1.7
Average Duration to Personnel Casualty



4-18

Figure 4.1.8
Average Duration to Personnel Casualty

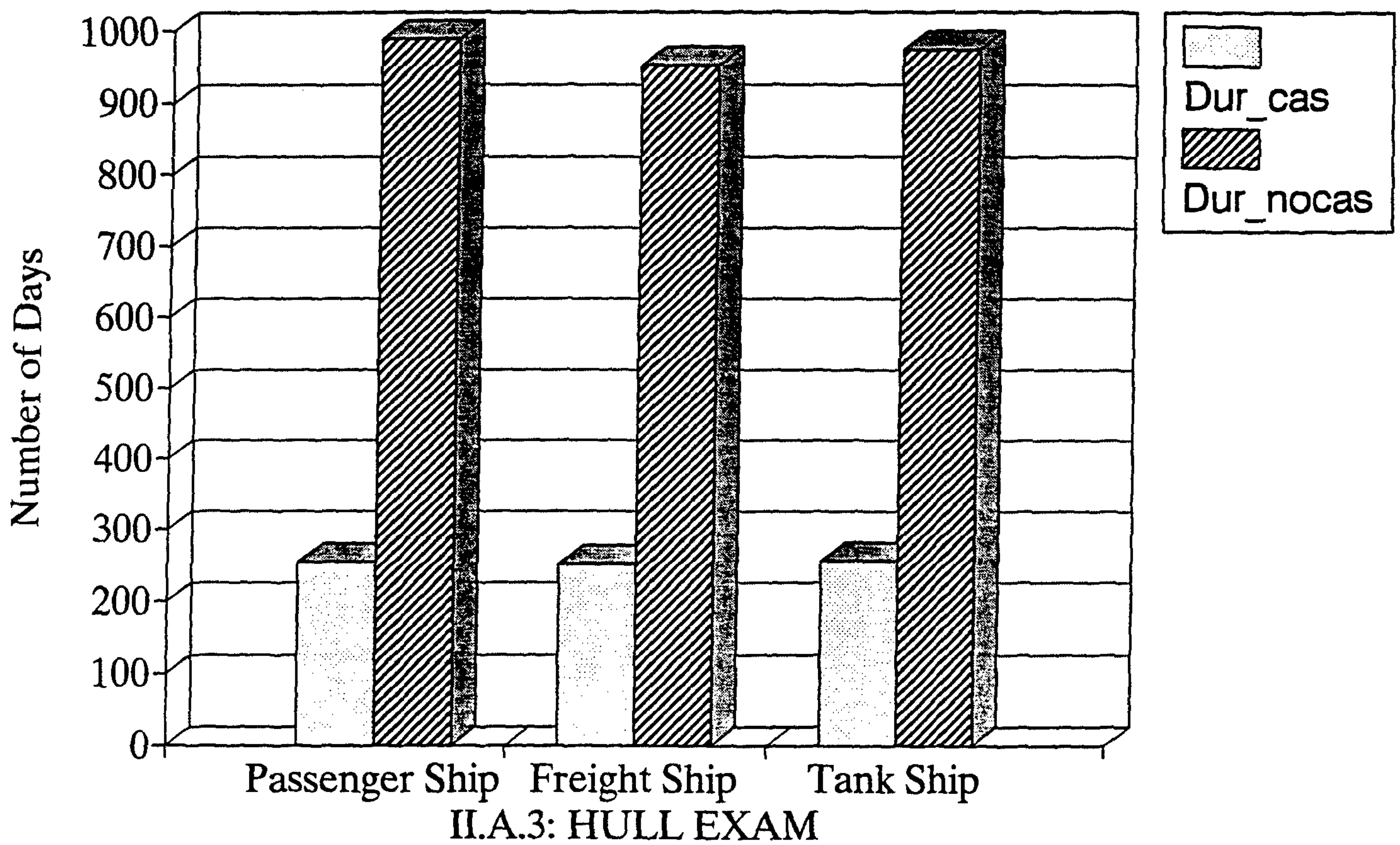


Figure 4.1.9
Average Duration to Pollution Casualty

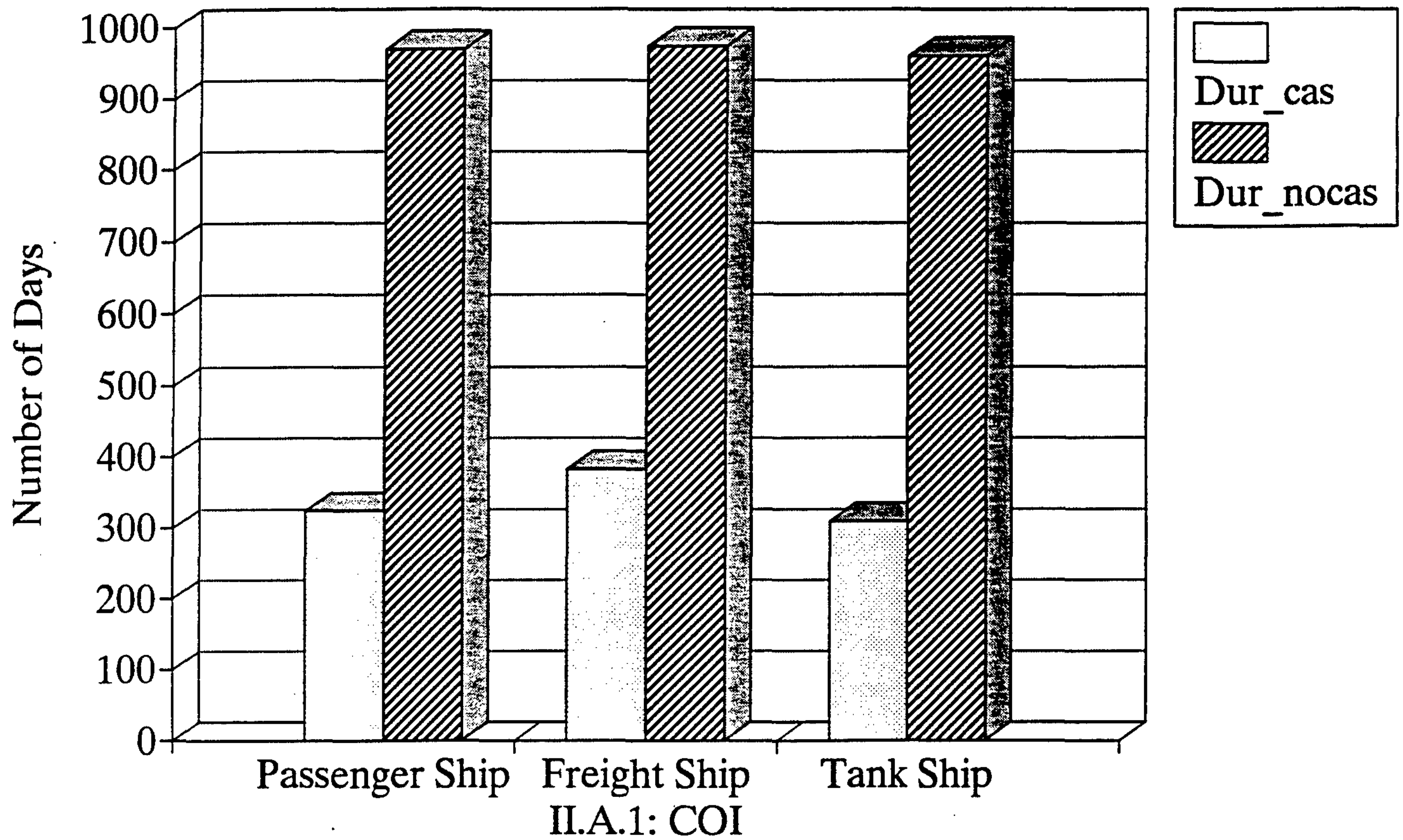


Figure 4.1.10
Average Duration to Pollution Casualty

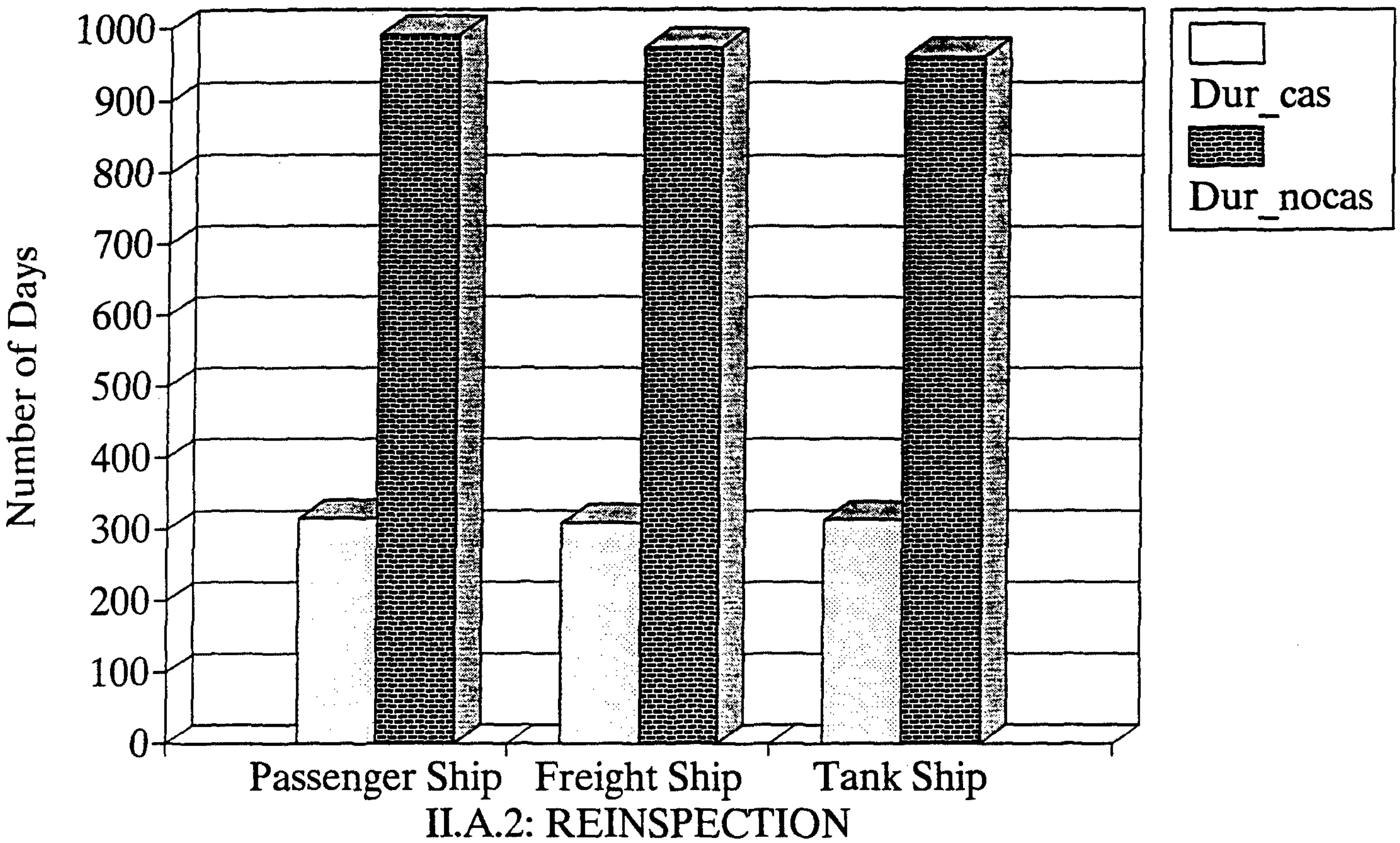
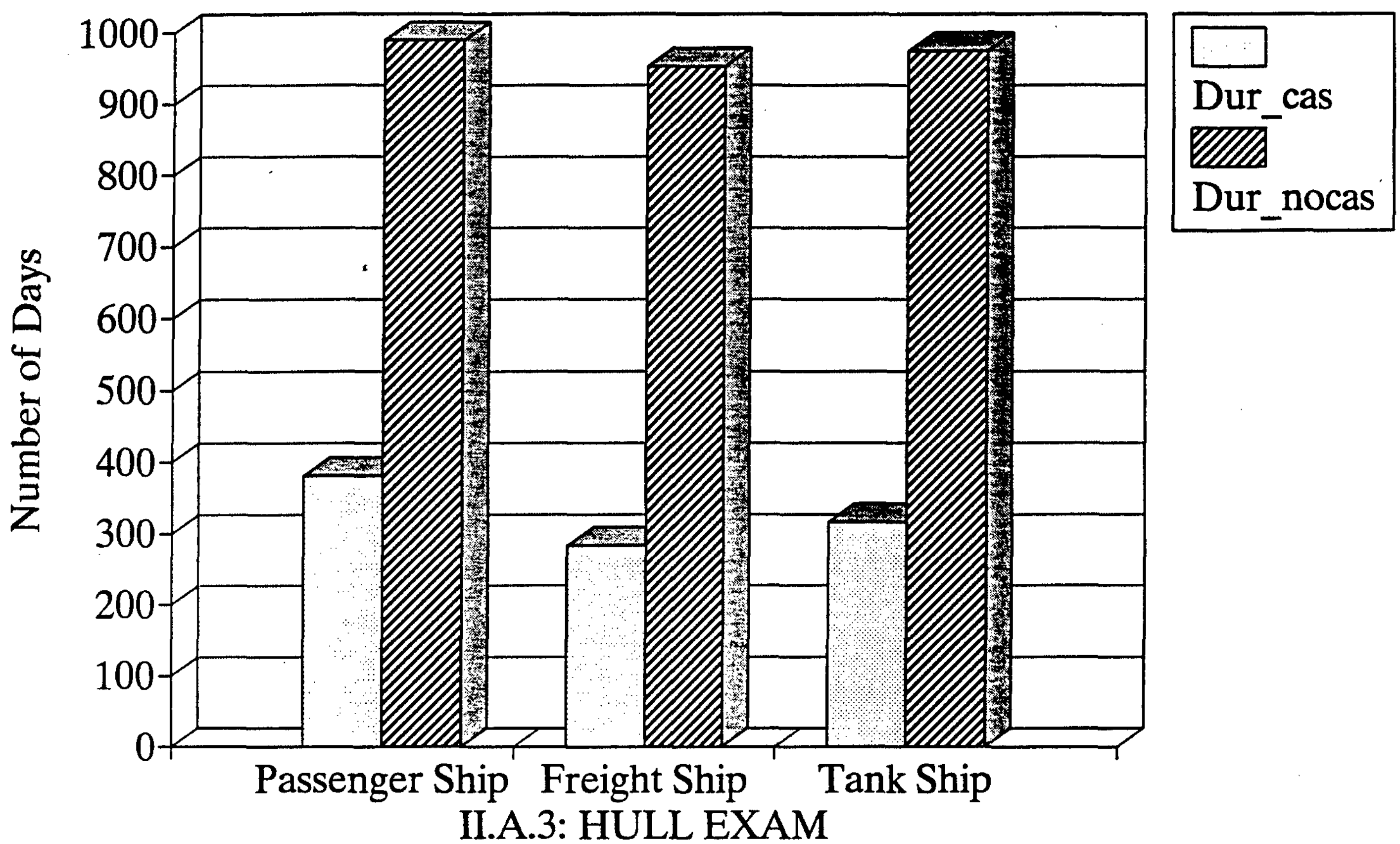


Figure 4.1.11

Average Duration to Pollution Casualty



4.4.2 Level I MOEs for U.S. Flag Deep-Draft Vessels from Poisson Models

i. Personnel Casualties: Deaths and Missing (D&M), and Injured

Level I MOEs measure the overall effectiveness of the Marine Inspection and Port Safety Program in an aggregate measure. We use the Poisson model to quantify the response of Personnel and Pollution Casualties to aggregate resources input by the USCG into this Program. From estimates of the coefficient on these aggregate hours, namely aggregate hull hours (HULL_HR), aggregate machinery hours (MACH_HR), and aggregate administration hours (ADMIN_HR), we can infer their effectiveness in reducing or controlling casualties. Table 4.1.1 presents estimates from a cross-sectional Poisson model of Personnel casualties. 951 deep draft U.S. flag vessels are covered in the cross-section. The "Deaths and Missing" (D&M) column reports the results where the dependent (or lhs) variable is the number of personnel deaths and missing reported (for each of the 951 vessels) between 1991 and 1993, and the "Injuries" column reports the results where the lhs variable is the number of personnel injuries between 1991 and 1993. A description of the variables is provided in Table 4.0. Estimation is by maximum likelihood.[7] Asterisks denote statistical significance, the log of the likelihood ratio (*LLR*) statistic measures the significance of the entire model, and a pseudo R-squared measure (*Mad.* R^2) provides a rough measure of fit. The *LLR* statistic is distributed as a chi-squared random variable. Since the critical value at the 5% level of the chi-squared statistic with 5 degrees of freedom is 11.07, clearly the model passes the basic test that the explanatory variable each do not have a coefficient equal to zero, that is, the model performs much better with the collection of variables than a model with just the intercept term. The pseudo R^2 statistic is low, but our model here is very parsimonious relative to the number of observations. As the number of variables increases in the estimating equations (or model specification), the R^2 measure also increases.

If USCG resources are effectively employed, we should see statistically significant negative coefficient estimates on those resources if there are a "significant" number of casualties in the data set. We wish to refer the reader to Section 2.2.3, and the discussion relevant to the case where there are very few casualties in the data set relative to the number of observations in the data set. For

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[7] All computations were performed on a HP 9000, 735 series UNIX platform. The matrix processing software GAUSS for UNIX v. 3.x.x. was employed to perform all statistical estimations. The Poisson models and Duration models are well-behaved nonlinear optimiztion problems, and convergence is fast. No model took longer than 2 minutes to converge. Alternatively, other statistical software may be used and provide a wider range of event count models (of which Poison is one) and Duration models to choose from. One package that is popular, powerful, and easy to use, is LIMDEP.

The data sets were constructed from the MSMS database tables using the same platform. The database software package used was INFORMIX-ISQL and INFORMX-4GL. ISQL is an SQL-based language and very close in logic to database packages such as SYBASE. Their syntax is quite similar although there are some differences. ISQL was used for the construction of most data sets. The time taken to construct the data sets ranged from 60 minutes for the U.S. flag aggregate resources and casualties data set to nearly 300 minutes for the Level III U.S. flag data set.

example, there are 14 observations (total number of D&M=24) in the data set of 951 observations in Table 4.1.1. Is this a small number or a significant enough number that we can conclude outright that the USCG is effective ? Do statistically insignificant coefficients mean that we cannot say anything about the USCG's effectiveness in reducing casualties? It may be hypothesized that if the number of casualties is low, then that is itself evidence that the USCG is effective to a large degree, and whatever casualties do happen, are largely random events. In this case coefficients on resources (as well as on other variables such as REG_GT and AGE) should show up as statistically insignificant. For the D&M column, although this is the case with the coefficients on HULL_HR and MACH_HR, the variables REG_GT and ADMIN_HR appear strongly positively. This refutes the hypothesis that most deaths and missing are purely random event. The positive coefficient on ADMIN_HR in fact indicates that administrative hours do not contribute to controlling deaths and missing. In the second column, however, MACH_HR is statistically significant and shown to be effective in reducing injuries. From the expression for the response in Section 4.3.1, an increase of 1000 machinery hours will reduce expected number of Injured by $\beta\times\lambda_i = \beta\times\exp(\beta' x_i)$ on vessel i. To obtain an average for the data set, we average λ_i over the 951 vessels, which works out to .538. Hence an increase of 1000 machinery hours will reduce the expected number of Injured by .238×.568=.135,[8] or 100,000 additional machinery hours will reduce Injured by about 13.5. Again ADMIN_HR is statistically significant and has the opposite sign. Indeed this is a constant feature of all the equations estimated and presents a puzzle. This puzzle is resolved subsequently.

Tables 4.1.2 and Tables 4.1.3 present results using different specifications of rhs variables. Although based on a well-founded theory, the true specification is really unknown, and the theory is silent on the precise form of the true specification. Therefore the presentation of results for a range of specifications indicate the robustness of results to variations in the specification. In both these tables, the *LLR* (likelihood ratio) statistic attests to the validity of the model. In Table 4.1.2, dummy variables (binary indicators) for Passenger vessels (DP) and Freight ships (DF) are added. For example, DP takes the value if the vessel is a Passenger vessel, and 0 otherwise. In graphical terms, inclusion of dummies has the effect of allowing different intercepts for each of the three services. The results clearly show that Passenger vessels and Freight ships both have a higher level of Personnel casualties than Tank ships *even after controlling for size, age, and inspection resources*. Table 4.1.3 presents each resource hour by service by multiplying each resource hour variable by the three service dummy variables. For example, MACH_P=MACH_HR×DP. In graphical terms these interaction terms allow differential coefficients on the resource hour variable across different services. The first column of Table 4.1.3 shows that hull hours are successful in preventing D&M casualties on Freight ships. The second column indicates that machinery hours are effective in preventing injuries on Passenger vessels, and machinery hours are effective in preventing injuries on Freight ships. The administrative hour puzzle remains, and in addition machinery hours have the opposite sign in the first column. Estimates on the dummy variables in the second column indicate that something other than the included variables is responsible for a higher incidence of injuries on Tank ships than the other services.

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[8] Therefore the average value of λi in the expression for the response in Section 4.3.1 is .568 here. Note that although this example is instructive, since the DSS graphs focus on such computations they are not performed for other estimates in this section.

The set of results contained in Tables 4.2.1-4.2.3 and 4.3.1-4.3.3 are motivated by the puzzling sign on the administrative hour variable (and sometimes other resource hour variables). Even before doing any estimation, our interactions with the USCG team comprising of LT Chris Rodriguez, LT Wyman Briggs, and Mr. Athar Pirzada had led us to consider the possibility of *positive* coefficients on the hour variables.[9] The reason for expecting positive coefficients is that when an inspection occurs, it is quite logical for a high number of hours to be spent on precisely those vessels that are likely to have higher casualties. Hence if we regress the number of casualties on resource hours, we actually capture this relationship in the positive coefficients. In econometrics this is known as the problem of *simultaneity* between a lhs and rhs variable. If simultaneity is present, a single equation is no longer appropriate for correct inference.[10] In order to rid the resource hour variables of simultaneity, we need an auxiliary regression that *predicts* each resource hour variable. The predictions from these auxiliary regressions is then substituted in place of the original resource hour variables, and the Poisson model estimated. This two-stage process is commonly used in simultaneous econometric model. Tables 4.2.1-4.2.3 present the results from this two-stage process.[11] The one striking difference is that HULL_HR is seen to be effective in reducing D&M, and this holds for the first column in Tables 4.2.1-4.2.3. From Table 4.2.3, it is seen that HULL_HR is effective in preventing D&M for Freight ships. However, the problem of positive coefficients on resource hour variables, particularly on ADMIN_HR, is not solved by this simultaneous equation estimation method.

The second approach to solving the problem of positive coefficients on resource hour variables is to consider the possibility that resource hours are highly correlated with REG_GT and/or AGE. If so, then the resource hour variables will pick up the effects of these other variables, rather than exhibiting their own effects. This problem can be solved by orthogonalizing each resource hour variable with respect to REG_GT and AGE. The residual from a linear regression of resource hours on these two variables achieves precisely that since residuals from a regression are constructed to be orthogonal to the rhs variables. Tables 4.3.1-4.3.3 display results from the Poisson model where the resource hour variables are replaced by their orthogonalized counterparts. The results are clearly very close to those in Table 4.1.1-4.1.3, probably because the fit on the regressions from which the residuals are taken is so poor that the residuals very closely resemble the original resource hour variables.

The third approach is one that is often applied in econometrics to prevent influential or "large" values

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[9] Epple and Visscher (1984) also faced the same problem in their preliminary estimates of determinants of oil pollution. However, their solution is different from ours.

[10] A simple example, much cited in economics, is if we regress price on quantity, we do not know whether we are estimating a demand relationship or a supply relationship.

[11] The auxiliary prediction regression uses the following variables on the rhs: number of deficiencies, number of COI inspections, number of Reinspections, number of Hull Exams, number of Administrative inspections, number of Initial inspections, number of Construction inspections, number of Defective inspections, number of Other inspections. These variables are consistent with the opinions from a survey of seven USCG officers with substantial inspection/boarding/examination experience. Although this auxiliary regression is not reported, the fit for each resource hour, HULL_HR, MACH_HR, and ADMIN_HR, is strong with R^2's .64, .59, and .84, respectively, and with signs on the variables consistent with the opinions of the officers surveyed.

of the rhs variables to determine the coefficients. (It is well known that "large" values exert undue influence over the position of a regression line since a regression line minimizes squared error and hence discourages large errors. Outlying values are therefore influential in the position of a regression line). There are two variations of this argument. One is that a few large outlier values can determine the outcome, and since the results are not representative of the sample (and therefore the population), the solution often adopted is to drop these outliers. Fortunately, our data set does not suffer from an outlier problem.[12] The second variation, and one that is more subtle and not easily recognized is that a regression may suffer from "scale effects" and give spurious results. An example is if we tried to explain the determinants of trade using data on imports and exports, and measures of labor and capital across countries. Clearly regressing trade (import + exports) will be greatly influenced by countries with large values of labor and capital stock, for example the U.S. The estimates are spurious on account of the scale effect, a problem often afflicting regressions that do not scale the rhs variables so they are "equal" across observations. In the above example, if the rhs variables are scaled by a measure of country size, for example GDP, then any observation (say, the U.S) is "equal" to another (say, Mexico). To prevent scale effects, we scale (divide) the resource hour variables by gross tonnage, REG_GT. These scaled hours are now used in the estimation. However, after scaling, the resource hour variables become highly collinear with correlation among them exceeding .85. This poses problems for estimation, but an even greater problem in terms of interpreting the results, since collinearity causes the coefficients to be extremely sensitive to specification changes and adding and dropping variables that are highly correlated. The natural solution, and one that we adopt here, is to include the resource variables one at a time rather than lump them all in a model.[13] These estimates are provided in Tables 4.4.1 and 4.4.2, and the results are striking. Six specifications are estimated in each table. In Table 4.4.1 although no significance at 10% is achieved, the first three columns come close to achieving statistical significance with the expected negative signs on all three resource hours. The *LLR* values attest to model adequacy, since they are all greater than their critical chi-squared values. In Table 4.4.2 the first three columns clearly shows that each resource hour is effective in reducing injuries, and are therefore resources well spent unless, of course, effort to reduce injuries costs more than the "value" of the injury reduction. Models 4, 5, and 6 indicate that Hull hours and Machinery hours are both effective in reducing injuries on Freight ships and Tank ships. Scaling also reverses the earlier results on Administrative hours, which are here shown to be effective in reducing injuries, particularly for Freight ships and Tank ships. Since the scaled resource hours are so highly correlated, it may be expected that their estimated coefficients will have similar patterns and this is borne out by the results here. From Tables 4.4.1 it is seen from the estimates of DP and DF in the first three columns that Passenger and Freight ships have larger intercepts that Tankships, but this conclusion is not robust to changes in specification. A robust result from Table 4.4.2 is that

[12] To find this out, we used the drop-one observation-at-a-time methodology recommended by Belsley, Kuh and Welsch (1980) to check for sensitivity of estimates to outliers. We estimated each model in Table 4.1.1-4.1.3 95 times, after dropping a block of 10 observations at a time (in descending order of REG_GT). An influential set of observations will be indicated by a large change in the size or sign of coefficient estimates. The estimates are surprisingly robust in this regard.

[13] Although in the unscaled case, the resource hour variables are correlated, their correlations do not exceed .6 and do not pose a problem. The collinearity is not per se caused due to the scaling. The collinearity problem in the PS cases, for example, is not nearly so severe.

the age of the vessel is inversely related to the number of personnel injured. U.S. deep-draft vessels are older compared to the world stock of deep-draft vessels, and it may be that they enjoy a longer life because they are better maintained than newer vessels. Or it may be true that the older the vessel the more careful the USCG inspections of these vessels. Both these arguments would support the negative coefficients on AGE.

For the remaining results, on both U.S. flag and Foreign flag vessels, we present estimates with resource hours unscaled as well as scaled by REG_GT. We omit further presentation of the simultaneous model or the model using orthogonalized resource hours, for they are not qualitatively very different from the results that we do present.

ii Pollution Casualties

In the analysis of Pollution casualties for U.S. flag deep-draft vessels, we drop from consideration Passenger vessels, since they account for only 9 of the 204 pollution occurrences between 1991 and 1993. Hence the data set comprises of 804 Freight ships and Tank ships. Table 4.5.1 presents results using unscaled resource hours. The first two columns show that MACH_HR is effective in reducing pollution occurrences. However the signs on HULL_HR and ADMIN_HR are counterintuitive. The third column offers no clear inferences. However, results using scaled hours presented in Table 4.5.2 are considerably sharper. The first three columns clearly indicate that all three resource hours are effective in reducing pollution casualties. The last three columns indicate that the resource hours are particularly effective on Tank ships (even though both services have almost equal number of pollution casualties in the data set). The coefficient estimates on resource hours possess the expected signs for Freight ships, but they are not statistically significant at the 10% level.

It may be relevant at this point to assess whether generally accepted statistical criteria such as 5% or 10% significance values should be blindly applied to the problem at hand. From our interactions with the USCG team and other USCG officers, we understand that a primary objective of USCG inspections is to prevent events of great significance, for example large oil spills. USCG inspection and boarding policy is thus necessarily conservative, since the "penalty" to err on the side of caution is the cost of excessive inspection hours, whereas the cost (in terms of reputation, morale, integrity of the USCG) is considerable. What does this imply about statistical significance criteria?
The hypothesis that is being tested by the *t*-statistics in the tables presented is the following:

H_0: β_{Hours} equals 0
H_1: β_{Hours} not equal to 0

or , verbally,

H_0: Hours (HULL, MACH, or ADMIN, respectively) do not affect casualties
H_1: Hours (HULL, MACH, or ADMIN, respectively) do affect casualties

Two types of errors can be made while testing this hypothesis, called Type I, and Type II errors, respectively. Type I error occurs when we reject a true null hypothesis, and Type II error occurs when we accept a false null hypothesis. The probability of Type I error is the probability of rejecting the null hypothesis, H_0, that is, the probability of making the erroneous inference that Hours do matter when in fact they don't. A Type I error leads to an erroneous decision to increase hours. Conventionally, Type I errors are considered "grave" errors, and the 5% or 10% cutoffs are meant to minimize this kind of error. But for the USCG, Type I error is an error on the side of caution and, as such, insignificant compared to a Type II error, which can have grave consequences. The probability of Type II error is the probability of accepting the null hypothesis, H_0, when in fact the null is false, that is, the probability of making the erroneous inference that Hours do not matter when in fact they do. The power of the test is [1 - Prob(Type II error)]. It is imperative that for the kind of decisions the USCG makes, we minimize Type II error, or what is the same thing, maximize the power of the test. It is well-known that there is a trade-off between the significance level (that is, the probability of Type I error) and the probability of Type II error. A small significance level (that is, probability of Type I error) will cause a larger probability of Type II error. Should we then adhere to the conventional 5% or 10% cutoffs in assessing whether USCG activities are effective in preventing casualties? We think not. Recognizing the extreme aversion to large casualties, and the effort of the USCG to minimize Type II error, we should apply a significance cutoff of 20%, maybe even 30% in assessing USCG effectiveness, simply because the USCG is willing to err on the side of caution to prevent Type II error. We recommend the use of a critical *t*-statistic of 1.00 (approximately 30% probability of Type I error for a two-tailed test, and 15% for a one-tailed test) to test the above hypotheses.[14]

By this standard, the last three columns in Table 4.5.2 show that Hull, Machinery, and Administrative

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[14] This discussion raises two issues. Firstly, that the casually held view of conventional 5% and 10% cutoffs as "objective" criteria is false. Their choice is in fact subjective and should suit the way in which decisions are made. Secondly, the power of the test is an important ingredient in making decisions, and the probability of Type I error must be reported in combination with the power function. This is beyond the scope of the present study, and is left for future implementation. Note that differential cutoffs can be applied. For example, in the case of Personnel casualties, for Deaths and Missing a 15% (in one tail) cutoff may be applied while a cutoff of 5% (in one tail) can be applied for Injured. This is recommended because Type II error in the case of D&M is of graver consequence than a Type II error in the case of Injured.

hours are each highly effective in reducing pollution occurrences by both Freight and Tank ships. Going back to Table 4.4.1, we see that Hull, Machinery, and Administrative hours are each highly effective in reducing Personnel D&M casualties, particularly in Passenger and Freight ships. Since the USCG desires to minimize Type II error with D&M casualties, which it considers a grave consequence, a low t-value of 1.00 is the appropriate critical value in testing effectiveness.

Table 4.0

Description of Variables

DEATHS	Number of deaths from a casualty. From CIRT.
MISSING	Number of missing from a casualty. From CIRT.
D&M	Number of deaths and missing from a casualty. From CIRT.
INJURED	Number of injuries from a casualty. From CIRT.
POLLOCCS	Number of pollution casualties. From CIRT.
DURCAS	Duration to casualty from last inspection. From CIRT, CRST.
DURNOCAS	Duration measure if no casualty. From CIRT, CRST.
REG_GT	Gross Tonnage of vessel. From VIDT.
AGE	Age of Vessel=1993-Year vessel built. From VIDT.
HULL_HR	Inspection hours on hull activities. '000 Hours. From CRST.
MACH_HR	Inspection hours on machinery activities. '000 Hours. From CRST.
ADMIN_HR	Administrative hours. '000 Hours. From CRST (MI), BRST (PS).
REG_HR	Examination hours by active duty personnel.'000 Hours. From BRST.
RES_HR	Examination hours by reserve personnel. '000 Hours. From BRST.
DF	Dummy variable. 1 if vessel is Freightship.
DP	Dummy variable. 1 if vessel is Passenger Ship.
DT	Dummy variable. 1 if vessel is Tankship.
hour_F	Hours (HULL, MACH, ADMIN, REG, RES) × DF
hour_P	Hours (HULL, MACH, ADMIN, REG, RES) × DP
hour_T	Hours (HULL, MACH, ADMIN, REG, RES) × DT

Note:

1. DEATHS, MISSING, INJURED, POLLOCCS are sum of casualties between 1991-1993.
2. HULL_HR, MACH_HR, ADMIN_HR, REG_HR, RES_HR are sum of resource hours between 1989-1993.

Table 4.1.1

MOEs from a Poisson Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag

Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable (y) Deaths and Missing	Injuries
Constant	-9.149 (-3.92)**	-2.949 (-8.62)**
Reg_gt	0.477 (2.19)**	0.246 (7.50)**
Hull_hr	-0.107 (-0.60)	0.016 (0.31)
Mach_hr	0.282 (0.90)	-0.238 (-2.60)**
Admin_hr	0.391 (1.73)*	0.442 (7.12)**
Age	0.010 (0.56)	-0.013 (-3.50)**
N	951	951
k	5	5
LLR	25.379	258.741
Mad. R^2	0.098	0.108
Obs. with *y*>0	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi- square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.1.2

MOEs from a Poisson Model of *Personnel* Casualties (MINMOD)
<u>MI Cases, U.S. Flag</u>

Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable (y): Deaths and Missing	Injuries
Constant	-14.653 (-3.97)**	-4.050 (-9.04)**
Reg_gt	0.843 (2.46)**	0.323 (7.46)**
Hull_hr	-0.286 (-1.20)	0.002 (0.04)
Mach_hr	0.251 (0.78)	-0.274 (-2.96)**
Admin_hr	0.572 (2.21)**	0.466 (7.32)**
Age	0.013 (0.71)	-0.013 (-3.46)**
DP	2.608 (2.05)**	0.725 (3.70)**
DF	2.347 (3.01)**	0.564 (5.53)**
N	951	951
k	7	7
LLR	40.539	294.00
Mad. R^2	0.156	0.122
Obs. with *y*>0	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi- square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.1.3

MOEs from a Poisson Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag

Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable (y): Deaths and Missing	lhs variable (y): Injuries
Constant	-12.187 (-3.14)**	-4.396 (-8.70)**
Reg_gt	0.758 (2.30)**	0.330 (7.34)**
Hull_P	0.272 (0.65)	0.120 (1.23)
Mach_P	-0.329 (-0.44)	-1.371 (-3.41)**
Admin_P	0.124 (0.17)	0.667 (4.69)**
Hull_F	-0.907 (-2.06)**	0.139 (1.47)
Mach_F	0.745 (2.29)**	-0.241 (3.52)**
Admin_F	1.027 (2.92)**	0.348 (3.52)**
Hull_T	0.850 (1.12)	0.053 (0.63)
Mach_T	-4.052 (-1.37)	-0.047 (-0.27)
Admin_T	0.787 (0.66)	0.409 (3.67)**
Age	0.013 (0.73)	-0.013 (-3.44)**
DP	1.527 (0.79)	1.536 (4.79)**
DF	0.178 (0.12)	0.772 (3.58)**
N	951	951
k	13	13
LLR	52.074	315.014
Mad. R^2	0.201	0.131
Obs. with y>0	14	247

Note:
(1) See Notes for Table **4.1.1**.

Table 4.2.1

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Predicted Hours from auxiliary regression
Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable *(y)*: Deaths and Missing	lhs variable *(y)*: Injuries
Constant	-12.728 (-3.90)**	-2.898 (-8.40)**
Reg_gt	0.831 (2.71)**	0.245 (7.19)**
Hull_hr	-3.458 (-3.28)**	-0.008 (-0.04)
Mach_hr	1.815 (1.06)	-0.130 (-0.36)
Admin_hr	2.531 (3.08)**	0.383 (2.00)**
Age	0.019 (1.06)	-0.013 (-3.56)**
N	951	951
k	5	5
LLR	42.022	223.019
Mad. R^2	0.162	0.093
Obs. with $y>0$	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.2.2

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Predicted Hours from auxiliary regression

Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable *(y)*: Deaths and Missing	lhs variable *(y)*: Injuries
Constant	-16.585 (-4.27)**	-4.027 (-8.96)**
Reg_gt	1.069 (2.90)**	0.324 (7.31)**
Hull_hr	-2.840 (-2.59)**	0.312 (1.42)
Mach_hr	0.416 (0.23)	-0.650 (-1.76)*
Admin_hr	2.798 (3.27)**	0.389 (1.99)**
Age	0.024 (1.32)	-0.013 (-3.48)**
DP	2.177 (1.88)*	0.799 (3.99)**
DF	1.928 (2.54)**	0.559 (5.30)**
N	951	951
k	7	7
LLR	52.211	256.391
Mad. R^2	0.201	0.107
Obs. with $y>0$	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.2.3

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Predicted Hours from auxiliary regression

Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

	lhs variable (y)	
rhs variables	Deaths and Missing	Injuries
Constant	-15.018 (-3.47)**	-4.808 (-9.36)**
Reg_gt	0.093 (2.47)**	0.333 (7.20)**
Hull_P	3.023 (1.32)	-0.747 (-1.44)
Mach_P	-5.085 (-0.78)	0.262 (.22)
Admin_P	0.683 (0.21)	0.646 (1.02)
Hull_F	-5.822 (-3.74)**	0.910 (2.74)**
Mach_F	2.054 (0.99)	-1.351 (-2.90)**
Admin_F	4.285 (4.01)**	0.289 (1.02)
Hull_T	-1.231 (-0.34)	-0.080 (-0.19)
Mach_T	-0.717 (-0.11)	1.223 (1.57)
Admin_T	1.827 (0.65)	-0.082 (-0.26)
Age	0.028 (1.53)	-0.012 (-3.10)**
DP	2.148 (0.93)	1.753 (4.96)**
DF	1.759 (0.91)	1.201 (4.44)**
N	951	951
k	13	13
LLR	66.965	281.875
Mad. R^2	0.258	0.117
Obs. with y>0	14	247

Note:
(1) See Notes for Table **4.2.1**.

Table 4.3.1

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Orthogonal to REG_GT and AGE
Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

	lhs variable *(y)*	
rhs variables	Deaths and Missing	Injuries
Constant	-9.0278 (-3.69)**	-2.711 (-7.82)**
Reg_gt	0.540 (2.37)**	0.269 (8.29)**
Hull_hr	-0.088 (-0.51)	0.015 (0.30)
Mach_hr	0.279 (0.90)	-0.242 (-2.64)**
Admin_hr	0.386 (1.71)*	0.441 (7.06)**
Age	0.005 (0.27)	-0.016 (-4.26)**
N	951	951
k	5	5
LLR	26.491	258.536
Mad. R^2	0.102	0.107
Obs. with y>0	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.3.2

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Orthogonal to REG_GT and AGE
Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable *(y)*: Deaths and Missing	Injuries
Constant	-14.321 (-3.87)**	-3.848 (-8.41)**
Reg_gt	0.885 (2.65)**	0.347 (8.25)**
Hull_hr	-0.273 (-1.17)	-0.007 (-0.13)
Mach_hr	0.245 (0.76)	-0.286 (-3.06)**
Admin_hr	0.573 (2.21)**	0.468 (7.28)**
Age	0.008 (0.44)	-0.016 (-4.17)**
DP	2.544 (2.02)**	0.750 (3.82)**
DF	2.304 (2.95)**	0.543 (5.33)**
N	951	951
k	7	7
LLR	40.937	291.841
Mad. R^2	0.158	0.121
Obs. with $y>0$	14	247

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.3.3

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Orthogonal to REG_GT and AGE
Cross Section of 951 Deep Draft Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable (y): Deaths and Missing	Injuries
Constant	-13.280 (-3.48)**	-3.968 (-8.14)**
Reg_gt	0.753 (2.24)**	0.359 (8.10)**
Hull_P	0.282 (0.67)	0.111 (0.75)
Mach_P	-0.314 (-0.43)	-1.101 (-3.21)**
Admin_P	0.116 (0.15)	0.665 (4.89)**
Hull_F	-0.889 (-2.09)**	0.134 (1.42)
Mach_F	0.738 (2.28)**	-0.245 (-1.95)*
Admin_F	1.051 (2.99)**	0.348 (3.51)**
Hull_T	0.676 (1.06)	-0.017 (-0.19)
Mach_T	-2.446 (-1.26)	-0.099 (-0.54)
Admin_T	0.710 (0.65)	0.417 (3.51)**
Age	0.007 (0.40)	-0.016 (-4.17)**
DP	3.045 (1.99)**	0.890 (4.07)**
DF	2.241 (2.06)**	0.552 (5.06)**
N	951	951
k	13	13
LLR	51.575	306.017
Mad. R^2	0.199	0.127
Obs. with y>0	14	247

Note:

(1) See Notes for Table **4.3.1**.

Table 4.4.1
MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Scaled by Gross Tonnage.
Cross Section of 951 Deep Draft Vessels
Dependent variable = Number of Personnel Deaths and Missing

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-4.573 (-5.90)**	-4.608 (-5.93)**	-4.566 (-5.89)**	-4.538 (-5.11)**	-4.042 (-3.70)**	-4.383 (-4.50)**
Hull_hr	-1.167 (-1.59)					
Mach_hr		-1.444 (1.57)				
Admin_hr			-1.033 (-1.58)			
Hull_P				-0.831 (-1.04)		
Mach_P					-1.326 (-1.11)	
Admin_P						-0.886 (-1.09)
Hull_F				-2.313 (-0.98)		
Mach_F					-1.462 (-1.01)	
Admin_F						-1.242 (-0.99)
Hull_T				-1.880 (-0.31)		
Mach_T					-17.655 (-0.61)	
Admin_T						-3.643 (-0.37)
Age	-0.007 (-0.52)	-0.008 (-0.58)	-0.008 (-0.56)	-0.006 (-0.44)	-0.008 (-0.54)	-0.008 (-0.52)
DP	2.148 (2.09)**	2.063 (2.05)**	2.134 (2.10)**	1.828 (1.48)	1.424 (1.05)	1.807 (1.40)
DF	1.732 (2.33)**	1.739 (2.34)**	1.723 (2.32)**	1.774 (1.99)**	1.164 (1.08)	1.549 (1.60)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	17.66	15.77	17.60	18.19	16.34	17.78
Obs. *y*>0	14	14	14	14	14	14

Table 4.4.2

MOEs from a Poisson Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Scaled by Gross Tonnage

Cross Section of 951 Deep Draft Vessels
Dependent variable = Number of Personnel Injuries

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.106 (-0.98)	-0.092 (-0.85)	-0.104 (-0.96)	0.127 (1.02)	0.050 (0.41)	0.058 (0.49)
Hull_hr	-0.212 (-5.03)**					
Mach_hr		-0.528 (-5.44)**				
Admin_hr			-0.169 (-4.80)**			
Hull_P				0.295 (5.13)**		
Mach_P					0.041 (0.35)	
Admin_P						0.161 (4.03)**
Hull_F				-0.534 (-4:36)**		
Mach_F					-1.076 (-4.26)**	
Admin_F						-0.612 (-4.34)**
Hull_T				-2.998 (-2.76)**		
Mach_T					-3.506 (-2.49)**	
Admin_T						-2.063 (-2.65)**
Age	-0.022 (-6.38)**	-0.023 (-6.58)**	-0.023 (-6.52)**	-0.022 (-6.12)**	-0.022 (-6.12)**	-0.021 (-5.91)**
DP	0.259 (1.62)	0.454 (2.71)**	0.260 (1.63)	-0.904 (-4.03)**	-0.275 (-1.27)	-0.667 (-3.19)**
DF	0.292 (2.94)**	0.305 (3.06)**	0.287 (2.89)**	0.115 (0.94)	0.193 (1.62)	0.178 (1.53)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	128.31	137.77	123.60	208.78	173.59	203.38
Obs. *y*>0	247	247	247	247	247	247

Table 4.5.1

MOEs from a Poisson Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag

Cross Section of 804 Deep Draft Vessels
Dependent variable *(y)* = Number of Pollution Incidents

rhs variables	Model 1	Model 2	Model 3
Constant	-3.535 (-6.22)**	-3.187 (-5.55)**	-3.120 (-5.29)**
Reg_gt	0.148 (2.65)**	0.134 (2.47)**	0.129 (2.37)**
Hull_hr	0.279 (3.34)**	0.260 (3.15)**	
Mach_hr	-0.330 (-2.16)**	-0.293 (-1.90)*	
Admin_hr	0.400 (3.57)**	0.378 (3.38)**	
Age	0.003 (0.52)	0.002 (0.42)	0.002 (0.41)
DF		-0.319 (-2.17)**	-0.382 (-1.31)
Hull_F			0.180 (1.04)
Mach_F			-0.323 (-1.42)
Admin_F			0.509 (2.83)**
Hull_T			-0.215 (-0.95)
Mach_T			-0.215 (-0.95)
Admin_T			0.292 (1.92)*
N	804	804	804
k	5	6	9
LLR	76.200	80.870	81.762
Mad. R^2	0.074	0.079	0.079
Obs. with *y*>0	144	144	144

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.5.2

MOEs from a Poisson Model of Pollution Casualties: MI Cases, U.S. Flag
Hours Scaled by Gross Tonnage.

Cross Section of 804 Deep Draft Vessels
Dependent variable *(y)* = Number of Pollution Incidents

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.837 (-5.35)**	-0.838 (-5.35)**	-0.830 (-5.30)**	-0.816 (-5.22)**	-0.826 (-5.27)**	-0.807 (-5.16)**
Hull_hr	-0.138 (-2.82)**					
Mach_hr		-0.258 (-2.51)**				
Admin_hr			-0.132 (-2.81)**			
Hull_F				-0.075 (-1.30)		
Mach_F					-0.178 (-1.34)	
Admin_F						-0.067 (-1.26)
Hull_T				-0.223 (-2.37)**		
Mach_T					-0.350 (-2.03)**	
Admin_T						-0.230 (-2.28)**
Age	-0.007 (-1.37)	-0.008 (-1.49)	-0.008 (-1.42)	-0.007 (-1.30)	-0.008 (-1.46)	-0.007 (-1.33)
DF	-0.551 (-3.85)**	-0.544 (-3.80)**	-0.553 (-3.86)**	-0.611 (-4.09)**	-0.579 (-3.87)**	-0.618 (-4.15)**
N	804	804	804	804	804	804
k	3	3	3	4	4	4
LLR	31.98	29.21	32.86	34.05	29.86	35.38
Obs. with *y*>0	144	144	144	144	144	14

4.4.3 Level II MOEs for U.S. Flag Deep-Draft Vessels from Duration Models

1. Activity II.A.1: COI

Duration to Personnel casualty is defined as the duration from a Level II activity to the closest casualty involving either personnel death, missing, or injury. No separate analysis is done for D&M and Injured as in the Poisson models. Duration to Pollution casualty is defined as the duration from a Level II activity to the closest casualty involving a pollution incident. For details on construction of the duration variable and the duration data sets the reader is referred to Section 4.2.2. The usefulness of the duration model lies in its ability to answer the question of how a change in the deployment of resource hours affects the time to a Personnel or Pollution casualty. The duration model is employed because Level II activities are naturally defined in terms of duration. A COI is required once every two years, Reinspections (Activity II.A.2) are required once every year, Hull Exams (Activity II.A.3) are required twice every five years with the requirement that not more that 3 years elapse between two inspections, and Annual Exams (Activity II.B.1-3) are required of Foreign flag vessels every year. Hence the effectiveness of these activities is best measured in how much longer they are able to prolong the event that a casualty occurs. Additionally, estimates from a duration model may form the basis of an economic decision of allocating resource hours by changing the duration over which these activities take place. For example, if a COI is shown to extend the expected duration to casualty by 2 years, then COIs may be carried out less frequently, thus saving resources. The converse argument can also be made to shorten the duration between two COIs. The results presented in the tables in this section provide MOEs for Level II activities in terms of the effectiveness of resource hours in extending the expected duration of a casualty.

Results from the duration analysis given that a Certificate of Inspection was performed is presented in Tables 4.6.1-4.6.3 for duration to Personnel Casualty since that activity, and in Tables 4.7.1-4.7.3 for duration to Pollution casualty since that activity. A *positive* coefficient on the resource hour variables conveys the information that USCG resources devoted to the COI activity is effective in prolonging time to casualty. Tables 4.6.1 and 4.6.2 contain estimates based on unscaled resource hours while Table 4.6.3 contains estimates using scaled hours. 1278 COI inspections between 1989 and 1993 are covered in the data set of which 585 were conducted on Freight ships, 332 on Passenger ships, and 361 on Tank ships. Table 4.6.1 shows strong support for the effectiveness of Machinery hours in increasing duration to a Personnel casualty, particularly on Freight ships and Tank ships. If we employ a critical *t*-value of 1.00, then Machinery hours are effective for all services. Although Hull hours exhibit the right sign, their standard errors are too large to make a strong inference from this unscaled data set. Administrative hours reappears with the opposite sign, and this question is further examined by scaling the data.[15] Model results based on subsets of the data set, split by vessel service are presented in Table 4.6.2. The results are very similar to those in Table 4.6.1. Results from the scaled model are presented in Table 4.6.3. Again, due to the high degree of correlation among the resource hour variables, the scaled models were estimated by including these variables one at a time. Using the usual 5% and 10% significance levels, Machinery hours and Administrative hours

[15] The simultaneous model and the model using orthogonalized hours are not reported here, but their results are not strikingly different, and the Administrative hour variable still has the wrong sign.

are both shown to be strongly effective in increasing time to Personnel casualty, particularly in Freight ships. If a 30% significance level is used (t=1.00) then each resource variable is effective in increasing time to Personnel casualty on vessels of almost all services.

The Pollution casualty results are weaker for the COI data set. Only Machinery hours are shown to be effective in Table 4.7.1, but this result is not robust across the different models in Tables 4.7.2 and 4.7.3. The scaled hour data set yields very weak inferences in Table 4.7.3

In sum, the COI activity is shown to favorably influence duration to Personnel casualty, but has little effect in prolonging duration to Pollution casualty.

2. Activity II.A.2: Reinspection

The duration data sets for Activity II.A.2 covers 1021 Reinspections between 1989 and 1993, of which 437 were conducted for Freight ships, 272 for Passenger ships, and 312 for Tank ships. Results based on the unscaled resource hour variables in Table 4.8.1 provide some inferences on the effectiveness of Reinspections in increasing time to Personnel casualty. The third column in Table 4.8.1 does indicate that Hull hours favorably affect Freight ships, and Machinery hours favorably affect Tank ships. Results in Table 4.8.2 based on observations disaggregated by service provide very weak inferences about effectiveness. However the data set with scaled hours indicates that all three resource hour variables are effective in prolonging time to Personnel casualty on vessels of each service (using a cutoff of t=1.00). This strong result attests to the overall effectiveness of Reinspections in increasing time to Personnel casualties.

The Pollution results are nowhere as strong. Results based on the unscaled variables in Table 4.9.1 and 4.9.2 provide weak inferences, if any. Results based on the scaled resource hours in Table 4.9.3 support the effectiveness of each resource hour in prolonging time to Pollution casualty only for Passenger vessels. But since Freight ships and Tank ships account for most pollution incidents, this result is probably less useful from a policy point of view.

Reinspections seem to be biased towards Passenger vessels in terms of their success in achieving their pollution safety goals. However, in terms of duration to Personnel casualty, Reinspections are successful for all services.

3. Activity II.A.3: Hull Exam

The duration data sets for Activity II.A.3 cover 856 Hull Exams between 1989 and 1993 of which

425 were conducted for Freight ships, 147 for Passenger ships, and 284 for Tank ships. We would certainly expect Hull hours, which is the largest component of a Hull Exam, to be effective in prolonging duration to casualty, and the results, particularly those based on scaled hours, fairly robustly allow such an inference for duration to Personnel and Pollution casualties. In Table 4.10.1 results based on unscaled hours strongly indicate that Machinery hours of a Hull Exam are effective in increasing the time to Personnel casualty on Tankers. Although the results for unscaled Hull hours are weak, the results based on scaled hours in Table 4.10.3 are strong and impressive. Hull hours, and indeed Administrative hours are effective in increasing time to Personnel casualty in vessels of all services, while Machinery hours are effective for Freight ships.

In Tables 4.11.1 and 4.11.2, unscaled Hull hours are shown to be effective in increasing duration to Pollution casualty, particularly for Freight ships (using a cutoff of t=1.00). Machinery hours devoted to a Hull Exam also favorably affect Tank ships. Results using scaled hours contained in Table 4.11.3 also corroborate the effectiveness of Hull hours particularly for Freight ships and Passenger ships, but reverse the results for Machinery hours, which are no longer effective for Tank ships, but are effective for Freight ships. The Administrative hours are now shown to favorably affect Passenger and Tank ships.

Clearly Hull Exams successfully achieve their safety goals in increasing time to Personnel as well as Pollution casualties. The results using scaled hours strongly attests to the effectiveness of each component resource hour of a Hull Exam.

Table 4.6.1
MOEs from an Exponential Duration Model of Personnel Casualties
MI Cases, U.S. Flag, 1991-1993
Cross Section of 1278 II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injured)

rhs variables	Model 1	Model 2	Model 3
Constant	7.164	7.155	7.141
	(103.32)**	(97.28)**	(94.22)**
Reg_gt	-0.054	-0.054	-0.055
	(-8.45)**	(-8.40)**	(-8.36)**
Hull_hr	0.147	0.155	
	(0.74)	(0.77)	
Mach_hr	0.893	0.890	
	(3.79)**	(3.78)**	
Admin_hr	-1.959	-1.970	
	(-4.91)**	(-4.95)**	
Age	0.002	0.002	.002
	(2.03)**	(2.05)**	(1.99)**
DP		0.007	0.056
		(0.20)	(0.84)
DF		0.057	0.038
		(0.45)	(0.61)
Hull_P			0.116
			(0.29)
Mach_P			0.834
			(1.49)
Admin_P			-2.241
			(-3.59)**
Hull_F			0.071
			(0.22)
Mach_F			0.864
			(2.87)**
Admin_F			-1.912
			(-3.06)**
Hull_T			0.177
			(0.48)
Mach_T			0.936
			(1.71)*
Admin_T			-1.848
			(-2.61)**
N	1278	1278	1278
k	5	7	13
LLR	28.06	28.11	28.36
Obs. with y>0	256	256	256

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.6.2

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injured)

rhs variables	Freight	Passenger	Tank
Constant	7.146 (66.59)**	7.300 (42.94)**	7.028 (52.95)**
Reg_gt	-0.052 (-5.62)**	-0.061 (-2.64)**	-0.049 (-4.48)**
Hull_hr	0.076 (0.23)	0.129 (0.32)	0.170 (0.46)
Mach_hr	0.844 (2.76)**	0.826 (1.44)	0.972 (1.84)*
Admin_hr	-1.899 (-3.03)**	-2.320 (-3.73)**	-1.901 (-2.73)**
Age	0.002 (1.32)	0.0001 (0.10)	.004 (2.16)**
N	585	332	361
k	5	5	5
LLR	11.38	3.86	10.04
Obs. with $y>0$	140	38	78

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.6.3

MOEs from an Exponential Duration Model of Personnel Casualties: MI Cases, U.S. Flag
Hours Scaled by Gross Tonnage.
Cross Section of 1,278 II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injured)

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.556 (237.11)**	6.555 (237.08)**	6.555 (236.92)**	6.555 (236.19)**	6.554 (236.20)**	6.554 (235.84)**
Hull_hr	0.025 (1.58)					
Mach_hr		0.038 (2.04)**				
Admin_hr			0.033 (2.06)**			
Hull_P				0.089 (1.04)		
Mach_P					0.093 (0.89)	
Admin_P						0.068 (0.67)
Hull_F				0.036 (1.51)		
Mach_F					0.065 (1.89)*	
Admin_F						0.047 (2.07)**
Hull_T				0.018 (0.96)		
Mach_T					0.027 (1.52)	
Admin_T						0.024 (1.29)
Age	0.005 (5.81)**	0.005 (5.81)**	0.005 (5.78)**	0.005 (5.51)**	0.005 (5.63)**	0.005 (5.57)**
N	1,278	1,278	1,278	1,278	1,278	1,278
k	2	2	2	4	4	4
LLR	8.42	8.50	8.57	8.54	8.63	8.63
Obs. *y*>0	256	256	256	256	256	256

Note:
1. See Notes for Table 4.6.1.

Table 4.7.1

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993

Cross Section of 1278 II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3
Constant	7.097	6.998	7.009
	(118.18)**	(107.41)**	(99.81)**
Reg_gt	-0.031	-0.027	-0.028
	(-5.63)**	(-4.55)*	(-4.43)**
Hull_hr	0.103	0.166	
	(0.53)	(0.89)	
Mach_hr	0.538	0.501	
	(1.95)*	(1.83)*	
Admin_hr	-1.443	-1.527	
	(-4.77)**	(-5.00)**	
Age	-0.0001	-0.0001	0.0000
	(-0.11)	(-0.10)	(-0.03)
DP		0.097	0.199
		(3.05)**	(2.03)**
DF		0.086	0.053
		(2.97)**	(1.00)
Hull_P			-0.039
			(-0.91)
Mach_P			0.705
			(1.42)
Admin_P			-1.919
			(-4.28)**
Hull_F			0.274
			(1.20)
Mach_F			0.307
			(0.80)
Admin_F			-1.243
			(-2.97)**
Hull_T			0.081
			(0.04)
Mach_T			0.819
			(1.24)
Admin_T			-1.814
			(-2.45)**
N	1278	1278	1278
k	5	7	13
LLR	9.12	11.08	11.58
Obs. with *y*>0	158	158	158

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.7.2

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Freight	Passenger	Tank
Constant	6.894 (75.93)**	7.357 (40.40)**	7.176 (55.72)**
Reg_gt	-0.010 (-1.34)	-0.057 (-2.23)**	-0.042 (-3.86)**
Hull_hr	0.302 (1.39)	-0.040 (-0.09)	0.054 (0.13)
Mach_hr	0.211 (0.56)	0.820 (1.64)	0.827 (1.28)
Admin_hr	-1.186 (-2.84)**	-2.020 (-4.50)**	-1.876 (-2.57)**
Age	0.0009 (0.74)	-0.0007 (-0.80)	-0.001 (-0.77)
N	585	332	361
k	5	5	5
LLR	2.00	2.86	4.24
Obs. with $y>0$	74	15	69

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.7.3

MOEs from an Exponential Duration Model of <u>Pollution</u> Casualties: MI Cases, U.S. Flag Hours Scaled by Gross Tonnage.

Cross Section of 1,278 II.A.1 Activities (COI)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.719 (319.59)**	6.719 (319.42)**	6.719 (319.47)**	6.719 (318.50)**	6.719 (318.27)**	6.719 ((318.35)**
Hull_hr	0.002 (0.17)					
Mach_hr		0.011 (0.76)				
Admin_hr			0.005 (0.36)			
Hull_P				0.028 (0.36)		
Mach_P					0.055 (0.62)	
Admin_P						-0.004 (-0.05)
Hull_F				0.007 (0.35)		
Mach_F					0.028 (0.95)	
Admin_F						0.008 (0.44)
Hull_T				-0.000 (-0.02)		
Mach_T					0.004 (0.26)	
Admin_T						0.003 (0.17)
Age	0.002 (2.92)**	0.002 (2.85)**	0.002 (2.90)**	0.002 (2.73)**	0.002 (2.67)**	0.002 (2.82)**
N	1,278	1,278	1,278	1,278	1,278	1,278
k	2	2	2	4	4	4
LLR	1.23	1.26	1.24	1.25	1.32	1.24
Obs. *y*>0	158	158	158	158	158	158

Note:
1. See Notes for Table **4.7.1**.

Table 4.8.1

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993

Cross Section of 1021 II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Model 1	Model 2	Model 3
Constant	7.362 (98.34)**	7.392 (91.09)**	7.503 (80.25)**
Reg_gt	-0.074 (-10.58)**	-0.069 (-9.63)**	-0.067 (-9.34)**
Hull_hr	-0.041 (-0.10)	0.047 (0.12)	
Mach_hr	0.050 (0.09)	-0.218 (-0.37)	
Admin_hr	-0.625 (-2.27)**	-0.748 (-2.62)**	
Age	-0.0005 (-0.49)	-0.001 (-0.98)	-0.0008 (-0.81)
DP		0.034 (0.75)	-0.113 (-1.23)
DF		-0.097 (-2.52)**	-0.036 (-0.36)
Hull_P			-1.253 (-1.45)
Mach_P			-0.441 (-0.39)
Admin_P			0.553 (1.62)
Hull_F			0.784 (1.53)
Mach_F			-1.188 (-1.13)
Admin_F			-3.074 (-4.61)**
Hull_T			-0.551 (-.96)
Mach_T			1.362 (2.00)**
Admin_T			-3.442 (-4.15)**
N	1021	1021	1021
k	5	7	13
LLR	23.35	25.93	35.67
Obs. with *y*>0	230	230	230

Note:
1. See Notes for Table **4.7.1**.

Table 4.8.2

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Freight	Passenger	Tank
Constant	7.593 (67.41)**	7.503 (32.83)**	7.170 (62.41)**
Reg_gt	-0.080 (-7.67)**	-0.074 (-2.40)**	-0.040 (-3.95)**
Hull_hr	0.724 (1.39)	-1.210 (-1.45)	-0.487 (-0.84)
Mach_hr	-1.003 (-0.94)	-0.481 (-0.44)	1.000 (1.33)
Admin_hr	-3.148 (-4.67)**	0.510 (1.49)	-3.448 (-4.16)**
Age	-0.001 (-0.78)	-0.003 (-1.73)*	.004 (2.22)**
N	437	272	312
k	5	5	5
LLR	17.41	4.87	9.91
Obs. with $y>0$	129	39	62

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.8.3

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag

Cross Section of 1,021 II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.587 (222.21)**	6.589 (222.92)**	6.583 (221.68)**	6.579 (220.59)**	6.581 (220.60)**	6.576 (220.60)**
Hull_hr	0.054 (2.38)**					
Mach_hr		0.060 (1.85)*				
Admin_hr			0.076 (3.51)**			
Hull_P				0.311 (3.92)**		
Mach_P					0.323 (3.93)**	
Admin_P						0.251 (4.68)**
Hull_F				0.087 (3.62)**		
Mach_F					0.119 (3.20)**	
Admin_F						0.091 (2.76)**
Hull_T				0.032 (1.36)		
Mach_T					0.025 (0.96)	
Admin_T						0.051 (2.23)**
Age	0.003 (2.90)**	0.003 (2.88)**	0.003 (2.79)**	0.002 (2.48)**	0.002 (2.52)**	0.002 (2.51)**
N	1,021	1,021	1,021	1,021	1,021	1,021
k	2	2	2	4	4	4
LLR	3.99	3.45	5.24	6.01	5.44	6.95
Obs. $y>0$	230	230	230	230	230	230

Note:
1. See Notes for Table 4.8.2.

Table 4.9.1

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993

Cross Section of 1021 II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3
Constant	7.145	7.025	7.145
	(109.05)**	(101.95)**	(77.97)**
Reg_gt	-0.036	-0.027	-0.024
	(-5.93)**	(-4.18)**	(-3.70)**
Hull_hr	0.067	0.176	
	(0.23)	(0.59)	
Mach_hr	-0.138	-0.387	
	(-0.33)	(-0.84)	
Admin_hr	-0.117	-0.329	
	(-0.57)	(-1.61)	
Age	-0.002	-0.002	-0.001
	(-1.93)*	(-1.95)*	(-1.65)*
DP		0.160	-0.057
		(4.02)**	(-0.64)
DF		0.074	0.090
		(2.31)**	(0.98)
Hull_P			0.584
			(1.16)
Mach_P			-1.093
			(-1.59)
Admin_P			0.258
			(1.21)
Hull_F			0.558
			(1.34)
Mach_F			-1.262
			(-1.56)
Admin_F			-2.031
			(-3.65)**
Hull_T			-0.418
			(-0.70)
Mach_T			0.559
			(0.75)
Admin_T			-2.592
			(-2.83)**
N	1021	1021	1021
k	5	7	13
LLR	5.07	7.59	13.17
Obs. with $y>0$	121	121	121

Note:
1. See Notes for Table **4.9.2**.

Table 4.9.2

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Freight	Passenger	Tank
Constant	7.167 (72.72)**	7.159 (37.17)**	7.129 (57.44)**
Reg_gt	-0.019 (-2.03)**	-0.026 (-0.99)	-0.024 (-2.36)**
Hull_hr	0.579 (1.37)	0.635 (1.21)	-0.412 (-0.69)
Mach_hr	-1.304 (-1.54)	-1.146 (-1.73)*	0.542 (0.71)
Admin_hr	-2.046 (-3.65)*	0.215 (0.93)	-2.566 (-2.80)**
Age	-0.0001 (-0.08)	-0.003 (-2.53)**	-0.0006 (-0.31)
N	437	272	312
k	5	5	5
LLR	5.19	1.26	3.36
Obs. with $y>0$	52	11	58

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.9.3

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage, MI Cases, U.S. Flag

Cross Section of 1,021 II.A.2 Activities (REINSPECTION)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.775 (286.70)**	6.775 (287.25)**	6.774 (285.88)**	6.770 (284.34)**	6.771 (285.02)**	6.769 (284.22)**
Hull_hr	0.008 (0.50)					
Mach_hr		0.003 (0.14)				
Admin_hr			0.003 (1.61)			
Hull_P				0.199 (3.11)**		
Mach_P					0.219 (3.41)**	
Admin_P						0.181 (4.18)**
Hull_F				0.023 (1.05)		
Mach_F					0.004 (0.12)	
Admin_F						0.016 (0.60)
Hull_T				-0.002 (-0.13)		
Mach_T					-0.011 (-0.56)	
Admin_T						0.017 (0.85)
Age	0.000 (0.18)	0.000 (0.25)	-0.000 (-0.00)	-0.000 (-0.17)	-0.000 (-0.12)	-0.000 (-0.28)
N	1,021	1,021	1,021	1,021	1,021	1,021
k	2	2	2	4	4	4
LLR	0.05	0.02	0.38	1.06	1.14	1.58
Obs. *y*>0	121	121	121	121	121	121

Note:
1. See Notes for Table 4.9.2.

Table 4.10.1

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993

Cross Section of 856 II.A.3 Activities (HULL EXAM)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Model 1	Model 2	Model 3
Constant	7.316	7.361	73053
	(80.82)**	(78.78)**	(74.75)**
Reg_gt	-0.066	-0.066	-0.065
	(-8.67)**	(-8.85)**	(-8.72)**
Hull_hr	0.155	0.135	
	(0.67)	(0.58)	
Mach_hr	0.799	0.757	
	(2.96)*	(2.84)**	
Admin_hr	-2.262	-2.142	
	(-4.04)**	(-3.81)**	
Age	0.001	0.0005	0.0005
	(0.85)	(0.45)	(0.44)
DP		-0.020	-0.073
		(-0.41)	(-0.67)
DF		-0.066	0.084
		(-1.62)	(1.14)
Hull_P			-0.140
			(-0.28)
Mach_P			0.132
			(0.19)
Admin_P			-0.177
			(-0.14)
Hull_F			0.283
			(0.82)
Mach_F			0.405
			(0.61)
Admin_F			-3.331
			(-4.32)**
Hull_T			0.191
			(0.45)
Mach_T			0.525
			(1.49)
Admin_T			-1.435
			(-1.54)
N	856	856	856
k	5	7	13
LLR	22.81	23.55	25.89
Obs. with *y*>0	188	188	188

Note:
(1) See Notes for Table 4.10.2

Table 4.10.2

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.3 Activities (HULL EXAM)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Freight	Passenger	Tank
Constant	7.502 (64.60)**	7.211 (27.39)**	7.099 (45.94)**
Reg_gt	-0.07180 (-7.18)**	-0.069 (-2.12)**	-0.0452 (-4.16)**
Hull_hr	0.281 (0.82)	-0.166 (-0.33)	0.157 (0.37)
Mach_hr	0.394 (0.60)	0.154 (0.22)	0.540 (1.59)
Admin_hr	-3.369 (-4.37)**	-0.105 (-0.08)	-1.357 (-1.43)
Age	-0.002 (-1.31)	0.002 (0.82)	.004 (1.87)*
N	425	147	284
k	5	5	5
LLR	14.23	1.55	7.25
Obs. with y>0	110	19	59

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.10.3

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag

Cross Section of 856 II.A.3 Activities (HULL)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing,Injured)

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.539 (199.63)**	6.537 (198.81)**	6.540 (199.65)**	6.540 (197.92)**	6.532 (198.16)**	6.543 (198.71)**
Hull_hr	0.049 (3.12)**					
Mach_hr		0.048 (1.05)				
Admin_hr			0.050 (2.75)**			
Hull_P				0.236 (2.26)**		
Mach_P					0.141 (0.47)	
Admin_P						0.318 (1.92)*
Hull_F				0.062 (3.17)**		
Mach_F					0.132 (3.11)**	
Admin_F						0.058 (2.09)**
Hull_T				0.038 (1.82)*		
Mach_T					-0.063 (-2.98)**	
Admin_T						0.046 (2.17)**
Age	0.004 (4.17)**	0.005 (4.77)**	0.005 (4.25)**	0.004 (3.67)**	0.005 (4.85)**	0.004 (3.63)**
N	856	856	856	856	856	856
k	2	2	2	4	4	4
LLR	6.50	5.34	6.07	7.04	6.37	6.50
Obs. *y*>0	188	188	188	188	188	188

Note:
(1) See Notes for Table **4.10.2**

Table 4.11.1

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993

Cross Section of 856 II.A.3 Activities (HULL EXAM)
Dependent variable (*y*) = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3
Constant	7.080	7.033	7.077
	(92.54)**	(86.87)**	(77.19)**
Reg_gt	-0.033	-0.030	-0.030
	(-4.90)**	(-4.29)**	(-4.30)**
Hull_hr	0.257	0.265	
	(1.57)	(1.66)*	
Mach_hr	0.169	0.183	
	(0.91)	(0.98)	
Admin_hr	-0.758	-0.808	
	(-1.90)*	(-2.02)**	
Age	-0.0009	-0.001	-0.001
	(-0.95)	(-1.08)	(-1.05)
DP		0.168	0.093
		(1.60)	(0.98)
DF		0.023	-0.067
		(0.62)	(-1.01)
Hull_P			0.290
			(0.87)
Mach_P			0.443
			(0.75)
Admin_P			-1.789
			(-1.75)*
Hull_F			0.416
			(2.19)**
Mach_F			-0.054
			(-0.13)
Admin_F			-0.336
			(-0.66)
Hull_T			-0.327
			(-0.79)
Mach_T			0.752
			(1.99)**
Admin_T			-0.738
			(-0.83)
N	856	856	856
k	5	7	13
LLR	4.64	5.02	6.23
Obs. with $y>0$	119	119	119

Note:
(1) See Notes for Table **4.11.2**

Table 4.11.2

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
MI Cases, U.S. Flag, 1991-1993, *By Service*

Cross Section of *N* II.A.3 Activities (HULL EXAM)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Freight	Passenger	Tank
Constant	6.975 (67.72)**	7.450 (25.86)**	7.171 (46.10)**
Reg_gt	-0.023 (-2.51)**	-0.081 (-2.07)**	-0.038 (-3.11)**
Hull_hr	0.413 (2.20)**	0.306 (0.91)	-0.298 (-0.71)
Mach_hr	-0.072 (-0.18)	0.637 (1.08)	0.763 (2.03)**
Admin_hr	-0.341 (-0.67)	-1.791 (-1.73)*	-0.845 (-0.93)
Age	-0.003 (-1.65)*	0.0006 (0.43)	-0.002 (-0.87)
N	425	147	284
k	5	5	5
LLR	1.92	1.77	2.42
Obs. with $y>0$	57	11	51

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.11.3

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag

Cross Section of 856 II.A.3 Activities (HULL)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	6.727 (256.51)**	6.726 (255.63)**	6.727 (256.67)**	6.728 (255.92)**	6.721 (256.31)**	6.730 (256.61)**
Hull_hr	0.022 (1.43)					
Mach_hr		-0.008 (-0.21)				
Admin_hr			0.021 (1.29)			
Hull_P				0.183 (1.86)*		
Mach_P					-0.039 (-0.19)	
Admin_P						0.217 (1.48)**
Hull_F				0.032 (1.84)*		
Mach_F					0.080 (2.13)**	
Admin_F						0.020 (0.86)
Hull_T				0.014 (0.61)		
Mach_T					-0.011 (-2.70)**	
Admin_T						0.023 (1.15)
Age	0.001 (0.96)	0.001 (1.32)	0.001 (1.01)	0.001 (0.57)	0.001 (1.47)	0.001 (0.57)
N	856	856	856	856	856	856
k	2	2	2	4	4	4
LLR	0.54	0.27	0.44	0.93	1.29	0.67
Obs. *y*>0	119	119	119	119	119	119

Note:
(1) See Notes for Table **4.11.2**

4.4.4 Level III MOEs for U.S. Flag Deep-Draft Vessels from Poisson Models

The mapping from inspection types in table CRST of the MSMS database into Level III activities is provided in Appendix D. Based on this mapping provided by USCG personnel, we create nine separate data sets for the nine Level III activities. The mapping is primarily used to compute the number of Hull, Machinery, and Administrative hours expended per deep draft vessel in the performance of each Level III activity. Although the Level III activities listed in Section 1 seem very distinct and separate from one another, this is not the case with the mapping of CRST inspection types into the 9 Level III activities. According to the mapping, although activities III.1 (Cargo/Poll. Handling/Pollution Control) and activity III.8 (Hull) are distinct in terms of resource hours expended per vessel, activities III.2-III.7 and III.9 (that is, Steering/Navigation, Documents/Paperwork, Drills/Human Factors, Auxiliary Systems, Power Plant, Fire Fighting and Prevention, and Life Saving) are *equivalent*. Use of the mapping leads to exactly the same number of resource hours for each vessel. This is a deficiency of the CRST definition of inspection types. These inspection types are probably the historic method of keeping data, and maybe operationally it is sensible for field personnel to identify their inspection work in terms of the CRST inspection types. However, if the Level III activities are the key activities from the point of view of policy making, the CRST inspection types should be segmented based upon these activity definitions. Or a separate column "Activity III" could be added to CRST to reflect this. However, the problem with including a separate new column is that field personnel would be further burdened by being required not only to report resource hours expended on each inspection type (as is being done presently) but additionally to report the resource hours expended on each Level III activity. If the mapping is any indication, since one inspection type maps into many Level III activities, this would require field personnel to input many rows of data for every inspection type. Hence our recommendation is a simple one, if it can be adequately implemented. We recommend a more sophisticated mapping which gives information about the *fraction* of hours from an inspection type that goes into each Level III activity (where 0 indicates that the inspection type does not involve that Level III activity). We understand that USCG inspectors do not work on the basis of any precise fractional division of hours among Level III activities while performing inspections, but we hope that a rough approximation is available. It may be possible to amend the CRST inspection types so that such a fractional mapping becomes more sensible.

In the analysis of Level III activities, we have used a fractional mapping. Where an inspection type maps into more than one Level III activity, say *n* activities, we proportionately apportion resource hours to those activities, so that each Level III activity gets $1/n$ of the hours expended towards that particular instance of performing the inspection type.[16]

Only those estimates based on scaled hours are reported. The results are impressive and strongly attest to the effectiveness of each Level III activity in reducing Personnel and Pollution casualty. A Poisson model of casualties, similar to those employed in assessing Level I effectiveness of Marine inspection of U.S. deep-draft vessels is employed here. The estimates are presented in Tables 4.12.1-4.12.3 (Activity III.1), Tables 4.13.1-4.13.3 (Activity III.2-7,9), and Tables 4.14.1-4.14.3 (Activity III.8). In these tables the variable names are rather cryptic and need explaining. In Table 4.12.1

[16] We express great appreciation for the mapping and refinements to it provided by LCDR Peggy Thurber. We think the mapping does serve our purpose adequately given the problems intrinsic to creating such a mapping.

"D31hhr" stands for Hull hours spent on activity III.1. Similarly "D31mhr" and D31ahr" stand for Machine and Admin hours. "H31_P" stands for Hull hours on Passenger vessels (If the vessel is not a Passenger vessel, this variable takes the value zero). The postscripts "_F" and "_T" indicate Freightship and Tankships, and the beginning letter "H", "M", and "A" indicate Hull, Machine, and Admin hours, respectively.

The tables show that Activity III.1 (Cargo/Poll. Handling/Pollution Control) is certainly effective in controlling pollution occurrences as evidenced by the statistically significant estimates in the first three columns of Table 4.12.3. If we use a critical *t*-value of 1.00 then the last 3 columns show that Hull hours, Machinery hours, and Administrative hours are all individually effective for vessels of each service. Further, Activity III.1 is effective in reducing Personnel casualties as well, as indicated by the estimates in Tables 4.12.1 and 4.12.2. Much the same pattern is in evidence for Activity III,2-7, 9 in Tables 4.14.1-4.14.3, and the estimates are close enough to the Activity III.1 tables that it may be suspected that the resource hours data are very similar, so that there is no real distinction between the two sets of results, one merely replicates the other. This underscores the need for a mapping that allows greater discrimination between the nine Level III activities. Estimates for Activity III.8 presented in Tables 4.14.1-4.14.3 are somewhat different in magnitude, but the pattern of results is the same, indicating a great degree of success in controlling pollution and personnel casualties.

We would like to make clear statements about the effectiveness of *each* of the nine Level III activities. This is important from a policy perspective, especially while making decisions about how to redistribute a fixed pie of resource hours among each activity so as to most effectively control casualties. But the mapping does not allow such a statement, particularly about those activities that are not effective. What the results *do* say is that III.1 and III.8 are very effective in controlling casualties. While this is an important conclusion it is a retrospective statement, not one on which future policy and optimizing decisions can be made. The Risk-Based-Ranking (RBR) results provide valuable companion results in this regard since they single out Level III activities that contribute most to "risk" of casualty. To the extent that the mapping upon which the RBR are based is more precise, the econometric results for Level III activities may be combined with the RBR as inputs into decision making.

Table 4.12.1
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.1
Dependent variable (y) = Number of Personnel Deaths and Missing

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-4.604 (-5.93)**	-4.613 (-5.94)**	-4.593 (-5.91)**	-4.361 (-4.32)**	-4.150 (-3.85)**	-4.312 (-4.26)**
D31hhr	-8.891 (-1.43)					
D31mhr		-13.910 (-1.53)				
D31ahr			-10.064 (-1.48)			
H31_P				-6.808 (-0.92)		
H31_F				-12.868 (-0.86)		
H31_T				-50.328 (-0.38)		
M31_P					-12.288 (-1.07)	
M31_F					-15.016 (-0.97)	
M31_T					-160.268 (-0.53)	
A31_P						-8.496 (-1.03)
A31_F						-11.691 (-0.93)
A31_T						-65.987 (-0.41)
Age	-0.008 (-0.54)	-0.009 (-0.59)	-0.008 (-0.55)	-0.008 (-0.51)	-0.008 (-0.55)	-0.008 (-0.52)
DP	1.891 (1.90)*	1.984 (2.00)**	1.934 (1.94)*	1.478 (1.16)	1.431 (1.08)	1.539 (1.21)
DF	1.713 (2.30)**	1.725 (2.32)**	1.701 (2.29)**	1.493 (1.50)	1.259 (1.18)	1.422 (1.42)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	16.20	15.54	16.28	16.57	16.01	16.58
Obs. y>0	14	14	14	14	14	14

Table 4.12.2
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.1
Dependent variable *(y)* = Number of Personnel Injured

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.105 (-0.96)	-0.098 (-0.90)	-0.099 (-0.92)	0.111 (0.89)	0.056 (0.47)	0.069 (0.58)
D31hhr	-2.071 (-4.89)**					
D31mhr		-4.655 (-5.17)**				
D31ahr			-2.110 (-4.75)**			
H31_P				1.558 (2.99)**		
H31_F				-4.250 (-4.20)**		
H31_T				-30.710 (-2.61)**		
M31_P					0.437 (0.45)	
M31_F					-10.034 (-4.12)**	
M31_T					-39.660 (-2.47)**	
A31_P						2.167 (4.39)**
A31_F						-7.458 (-4.16)**
A31_T						-24.652 (-2.57)**
Age	-0.023 (-6.41)**	-0.023 (-6.61)**	-0.023 (-6.45)**	-0.022 (-6.21)**	-0.022 (-6.20)**	-0.022 (-6.20)**
DP	0.236 (1.48)	0.040 (2.40)**	0.233 (1.46)	-0.572 (-2.79)**	-0.277 (-1.35)	-0.648 (-3.19)**
DF	0.285 (2.87)**	0.297 (2.98)**	0.273 (2.75)**	0.106 (0.88)	0.173 (1.47)	0.176 (1.54)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	130.00	132.21	125.54	184.56	171.11	202.07
Obs. *y*>0	247	247	247	247	247	247

Table 4.12.3
MOEs from a Poisson Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.1
Dependent variable (y) = Number of Pollution Incidents

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.811 (-5.30)**	-0.804 (-5.25)**	-0.797 (-5.20)**	-0.787 (-5.15)**	-0.799 (-5.21)**	-0.783 (-5.11)**
D31hhr	-1.147 (-2.66)**					
D31mhr		-3.377 (-2.85)**				
D31ahr			-1.738 (-2.95)**			
H31_P				-1.600 (-0.63)		
H31_F				-0.507 (-1.06)		
H31_T				-2.070 (-2.30)**		
M31_P					-15.106 (-2.04)**	
M31_F					-2.464 (-1.62)	
M31_T					-3.223 (-1.99)**	
A31_P						-9.781 (-1.88)*
A31_F						-0.908 (-1.30)
A31_T						-2.277 (-2.24)**
Age	-0.009 (-1.71)*	-0.009 (-1.71)*	-0.009 (-1.63)	-0.009 (-1.64)	-0.008 (-1.77)*	-0.009 (-1.63)
DP	-1.507 (-4.26)**	-1.356 (-3.76)**	-1.463 (-4.11)*	-1.482 (-3.06)**	-0.660 (-1.40)	-0.780 (-1.63)
DF	-0.557 (-3.89)**	-0.548 (-3.83)**	-0.569 (-3.97)**	-0.621 (-4.19)**	-0.562 (-3.78)**	-0.613 (-4.14)**
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	57.75	60.96	69.34	60.62	64.90	68.47
Obs. $y>0$	151	151	151	151	151	151

Table 4.13.1
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.2-7,9
Dependent variable *(y)* = Number of Personnel Deaths and Missing

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-4.608 (-5.94)**	-4.614 (-5.94)**	-4.595 (-5.92)**	-4.404 (-4.50)**	-4.163 (-3.86)**	-4.322 (-4.29)**
D32hhr	-9.024 (-1.44)					
D32mhr		-13.994 (-1.54)				
D32ahr			-10.019 (-1.48)			
H32_P				-6.920 (-0.94)		
H32_F				-12.846 (-0.88)		
H32_T				-44.063 (-0.36)		
M32_P					-12.268 (-1.08)	
M32_F					-15.320 (-0.98)	
M32_T					-157.396 (-0.52)	
A32_P						-8.496 (-1.03)
A32_F						-11.574 (-0.93)
A32_T						-64.405 (-0.40)
Age	-0.008 (-0.53)	-0.009 (-0.58)	-0.008 (-0.55)	-0.007 (-0.50)	-0.008 (-0.55)	-0.008 (-0.52)
DP	1.894 (1.90)*	1.982 (2.00)**	1.933 (1.94)*	1.526 (1.22)	1.436 (1.09)	1.549 (1.22)
DF	1.708 (2.30)**	1.724 (2.32)**	1.701 (2.29)**	1.528 (1.57)	1.270 (1.19)	1.430 (1.44)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	15.89	15.45	16.25	16.21	15.90	16.54
Obs. *y*>0	14	14	14	14	14	14

Table 4.13.2
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.2-7,9
Dependent variable *(y)* = Number of Personnel Injured

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.102 (-0.94)	-0.099 (-0.92)	-0.100 (-0.93)	0.121 (0.97)	0.050 (0.42)	0.066 (0.56)
D32hhr	-2.253 (-4.96)**					
D32mhr		-4.631 (-5.09)**				
D32ahr			-2.121 (-4.79)**			
H32_P				2.218 (3.91)**		
H32_F				-5.514 (-4.16)**		
H32_T				-35.054 (-2.65)**		
M32_P					0.795 (0.77)	
M32_F					-10.241 (-4.10)**	
M32_T					-38.855 (-2.45)**	
A32_P						2.167 (4.39)**
A32_F						-7.426 (-4.15)**
A32_T						-24.362 (-2.54)**
Age	-0.023 (-6.41)**	-0.023 (-6.59)**	-0.023 (-6.45)**	-0.022 (-6.16)**	-0.022 (-6.18)**	-0.022 (-6.21)**
DP	0.250 (1.57)	0.391 (2.36)**	0.235 (1.47)	-0.701 (-3.30)**	-0.314 (-1.50)	-0.644 (-3.18)**
DF	0.280 (2.82)**	0.294 (2.96)**	0.274 (2.75)**	0.102 (0.84)	0.177 (1.51)	0.178 (1.56)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	128.36	130.00	125.12	194.54	169.67	201.46
Obs. *y*>0	247	247	247	247	247	247

Table 4.13.3
MOEs from a Poisson Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.2-7,9
Dependent variable (*y*) = Number of Pollution Incidents

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.805 (-5.26)**	-0.805 (-5.26)**	-0.798 (-5.21)**	-0.790 (-5.16)**	-0.800 (-5.22)**	-0.783 (-5.11)**
D32hhr	-1.481 (-2.88)**					
D32mhr		-3.343 (-2.81)**				
D32ahr			-1.759 (-2.98)**			
H32_P				-5.922 (-1.49)		
H32_F				-0.716 (-1.16)		
H32_T				-2.135 (-2.35)**		
M32_P					-15.046 (-2.05)**	
M32_F					-2.371 (-1.55)	
M32_T					-3.224 (-1.99)**	
A32_P						-9.780 (-1.88)*
A32_F						-0.903 (-2.29)**
A32_T						-2.330 (-2.29)**
Age	-0.009 (-1.66)*	-0.009 (-1.70)*	-0.009 (-1.63)	-0.009 (-1.62)	-0.009 (-0.76)	-0.009 (-1.62)
DP	-1.482 (-4.18)**	-1.363 (-3.87)**	-1.460 (-4.11)**	-1.038 (-2.13)**	-0.666 (-1.42)	-0.780 (-1.63)
DF	-0.562 (-3.92)**	-0.550 (-3.84)**	-0.568 (-3.97)**	-0.614 (-4.14)**	-0.566 (-3.80)**	-0.614 (-4.14)**
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	59.68	60.48	63.08	63.18	64.49	68.30
Obs. *y*>0	151	151	151	151	151	151

Table 4.14.1
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.8
Dependent variable *(y)* = Number of Personnel Deaths and Missing

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-4.593 (-5.93)**	-4.620 (-5.95)**	-4.598 (-5.93)**	-4.411 (-4.43)**	-4.036 (-3.79)**	-4.310 (-4.23)**
D38hhr	-7.575 (-1.50)					
D38mhr		-11.445 (-1.50)				
D38ahr			-7.206 (-1.49)			
H38_P				-4.763 (-0.89)		
H38_F				-18.187 (-0.98)		
H38_T				-32.802 (-0.33)		
M38_P					-9.921 (-1.02)	
M38_F					-12.337 (-0.97)	
M38_T					-184.212 (-0.63)	
A38_P						-4.823 (-0.87)
A38_F						-12.032 (-0.93)
A38_T						-51.593 (-0.41)
Age	-0.008 (-0.52)	-0.009 (-0.58)	-0.008 (-0.52)	-0.007 (-0.46)	-0.008 (-0.55)	-0.007 (-0.48)
DP	1.934 (1.94)*	1.939 (1.95)*	1.891 (1.90)*	1.459 (1.15)	1.253 (0.95)	1.357 (1.05)
DF	1.698 (2.28)**	1.722 (2.32)**	1.691 (2.27)**	1.603 (1.61)	1.134 (1.08)	1.434 (1.42)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	16.17	14.89	15.74	17.05	15.59	16.36
Obs. *y*>0	14	14	14	14	14	14

Table 4.14.2
MOEs from a Poisson Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.8
Dependent variable (y) = Number of Personnel Injured

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.131 (-1.21)	-0.091 (-0.84)	-0.129 (-1.19)	0.191 (1.53)	0.052 (0.43)	0.086 (0.74)
D38hhr	-0.559 (-2.77)**					
D38mhr		-4.750 (-5.25)**				
D38ahr			-0.605 (-2.78)**			
H38_P				3.865 (11.16)**		
H38_F				-2.360 (-3.80)**		
H38_T				-23.765 (-2.42)**		
M38_P					-0.006 (-0.01)	
M38_F					-9.504 (-4.05)**	
M38_T					-33.101 (-2.56)**	
A38_P						1.909 (9.22)**
A38_F						-3.931 (-4.18)**
A38_T						-16.595 (-2.48)**
Age	-0.024 (-6.87)**	-0.023 (-6.62)**	-0.024 (-6.81)**	-0.027 (-7.06)**	-0.022 (-6.21)**	-0.024 (-6.44)**
DP	0.128 (0.83)	0.433 (2.60)**	0.129 (0.83)	-1.479 (-6.18)**	-0.218 (-1.08)	-0.800 (-4.14)**
DF	0.288 (2.90)**	0.299 (3.00)**	0.279 (2.80)**	0.079 (0.65)	0.181 (1.55)	0.158 (1.41)
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	91.34	136.03	91.25	254.90	169.95	220.30
Obs. $y>0$	247	247	247	247	247	247

Table 4.14.3
MOEs from a Poisson Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. MI Cases, U.S. Flag
Hours Devoted to Activity III.8
Dependent variable *(y)* = Number of Pollution Incidents

rhs variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.810 (-5.29)**	-0.810 (-5.29)**	-0.806 (-5.27)**	-0.783 (-5.14)**	-0.791 (-5.17)**	-0.777 (-5.09)**
D38hhr	-0.894 (-2.46)**					
D38mhr		-2.098 (-2.43)**				
D38ahr			-1.604 (-2.63)**			
H38_P				-5.152 (-1.60)		
H38_F				-0.204 (-0.55)		
H38_T				-1.766 (-2.37)**		
M38_P					-11.878 (-1.95)*	
M38_F					-0.827 (-0.83)	
M38_T					-3.017 (-1.96)**	
A38_P						-7.535 (-1.88)*
A38_F						-0.207 (-0.44)
A38_T						-1.834 (-2.31)**
Age	-0.009 (-1.79)*	-0.010 (-1.85)*	-0.009 (-1.72)*	-0.009 (-1.66)*	-0.010 (-1.85)*	-0.009 (-1.68)*
DP	-1.495 (-4.23)**	-1.424 (-3.99)**	-1.482 (-4.19)**	-0.968 (-1.98)**	-0.734 (-1.53)	-0.766 (-1.58)
DF	-0.556 (-3.88)**	-0.547 (-3.82)**	-0.566 (-3.95)**	-0.642 (-4.31)**	-0.600 (-4.02)**	-0.647 (-4.33)**
N	951	951	951	951	951	951
k	4	4	4	6	6	6
LLR	54.29	54.77	56.43	61.11	60.05	64.28
Obs. *y*>0	151	151	151	151	151	151

4.5 Foreign Flag Vessels: Econometric Results and Level I, and II MOEs

4.5.1 Data Description: Examination/Boarding of Foreign Flag Deep-Draft Vessels

Figures 4.0.4-4.0.6 display the number of Personnel and Pollution casualties during 1991-1993 for Foreign flag deep-draft vessels examined/boarded by the USCG. 90% of the D&M casualties occur on Freight ships, while Injured casualties are more evenly distributed. Most Pollution casualties are attributable to Freight ships (about 55%) and Tank ships (about 40%), as may be expected. Compared to the number of Foreign flag vessels boarded/examined, shown in Figure 4.2.1, the number of casualties may seem quite small. A total of 10909 Foreign flag vessels appear in the econometric analysis, most of whom are Freight ships (76%) and Tank ships (22%). Resource hours devoted to Port Safety (PS) hours appear in Table 4.2.2 and 4.2.3. In the econometric analysis we employ regular active-duty personnel hours (REG_HR), hours by reserve personnel (RES_HR), and Administrative hours (ADMIN_HR). It is clear that hours devoted to PS cases is a major component of USCG activities, about three- or four-fold greater than MI (U.S. flag) cases. Figures 4.2.4 and 4.2.5 show that Foreign flag deep-draft vessels are, on average, both larger in terms of gross-tonnage and younger (by more than 10 years) than U.S. flag deep-draft vessels. Duration data in Figures 4.2.6 and 4.2.7 indicate that on average, if there is a casualty, it occurs about 250 days after an Annual Exam for a Personnel or Pollution casualty.

Figure 4.0.4
PS Cases:Number DEAD & MISSING, 1991-93

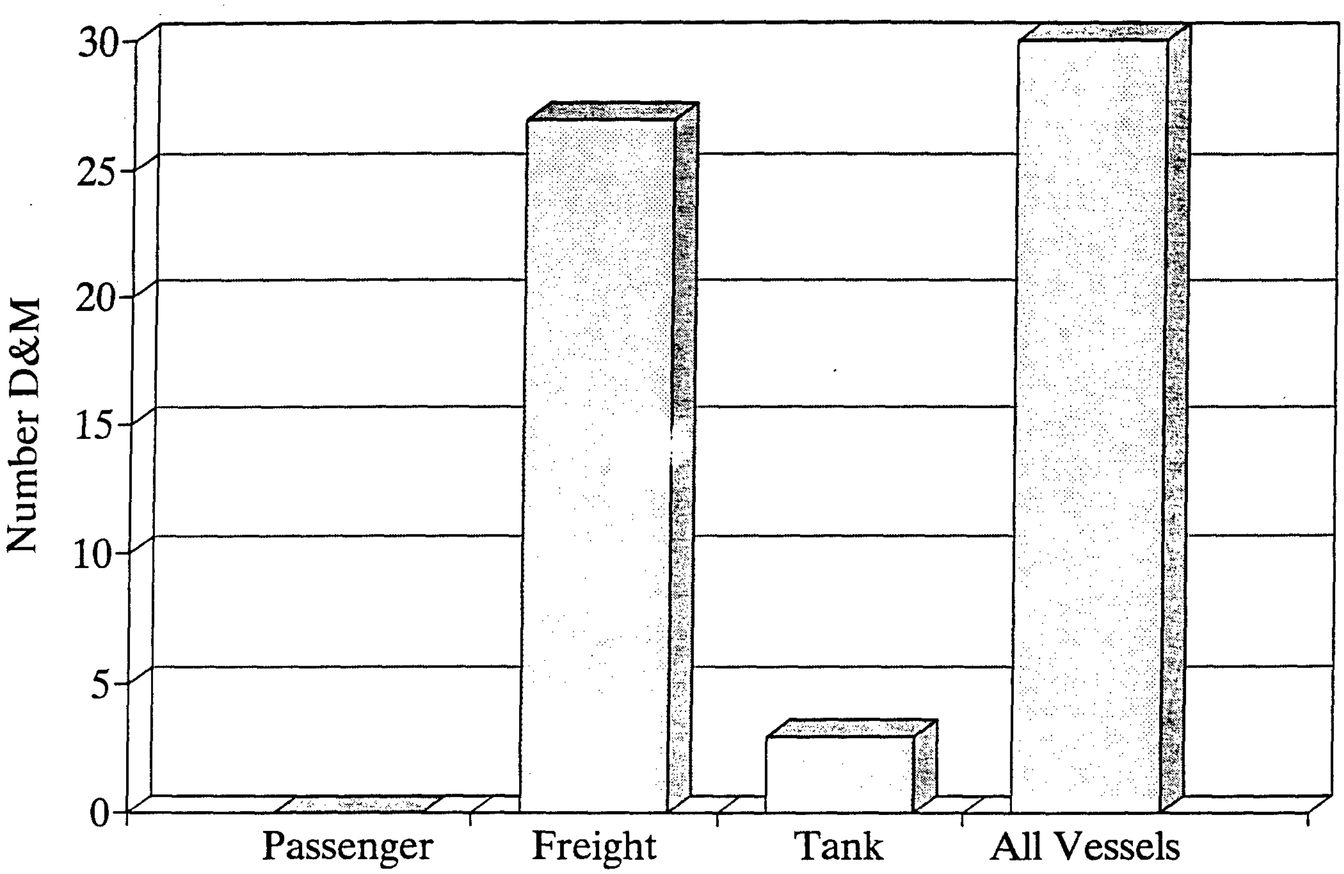


Figure 4.0.5

PS Cases: Number INJURED, 1991-1993

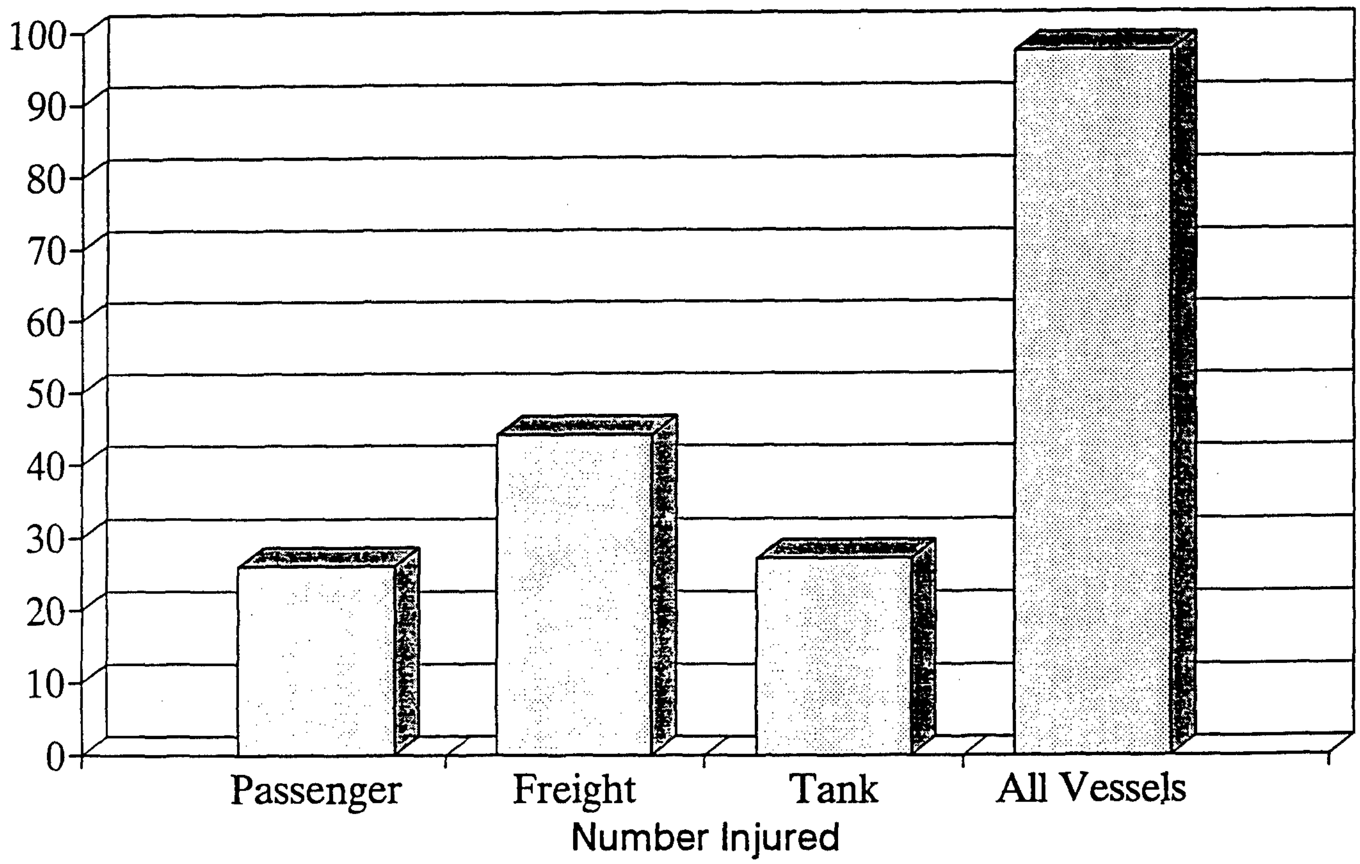


Figure 4.0.6
PS Cases: POLLUTION Casualties, 1991-93

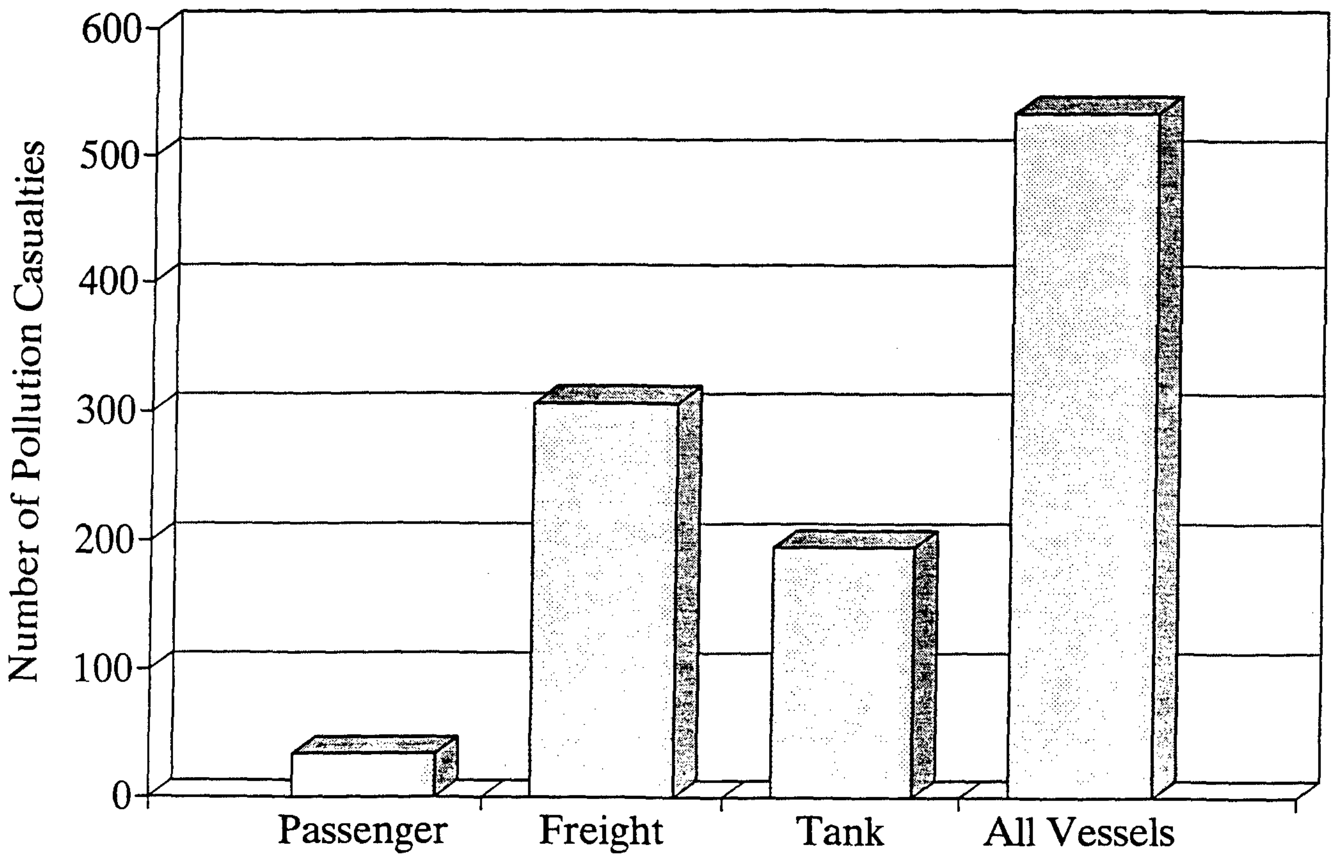
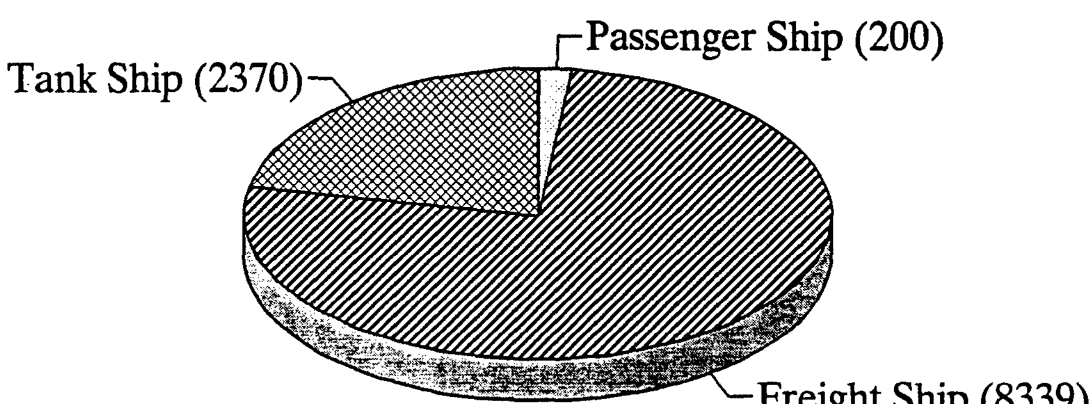


Figure 4.2.1

Deep Draft Vessels, PS Cases, Foreign Flag



Total = 10,909

Figure 4.2.2

Total Port Safety Hours, PS Cases, 1989-1993

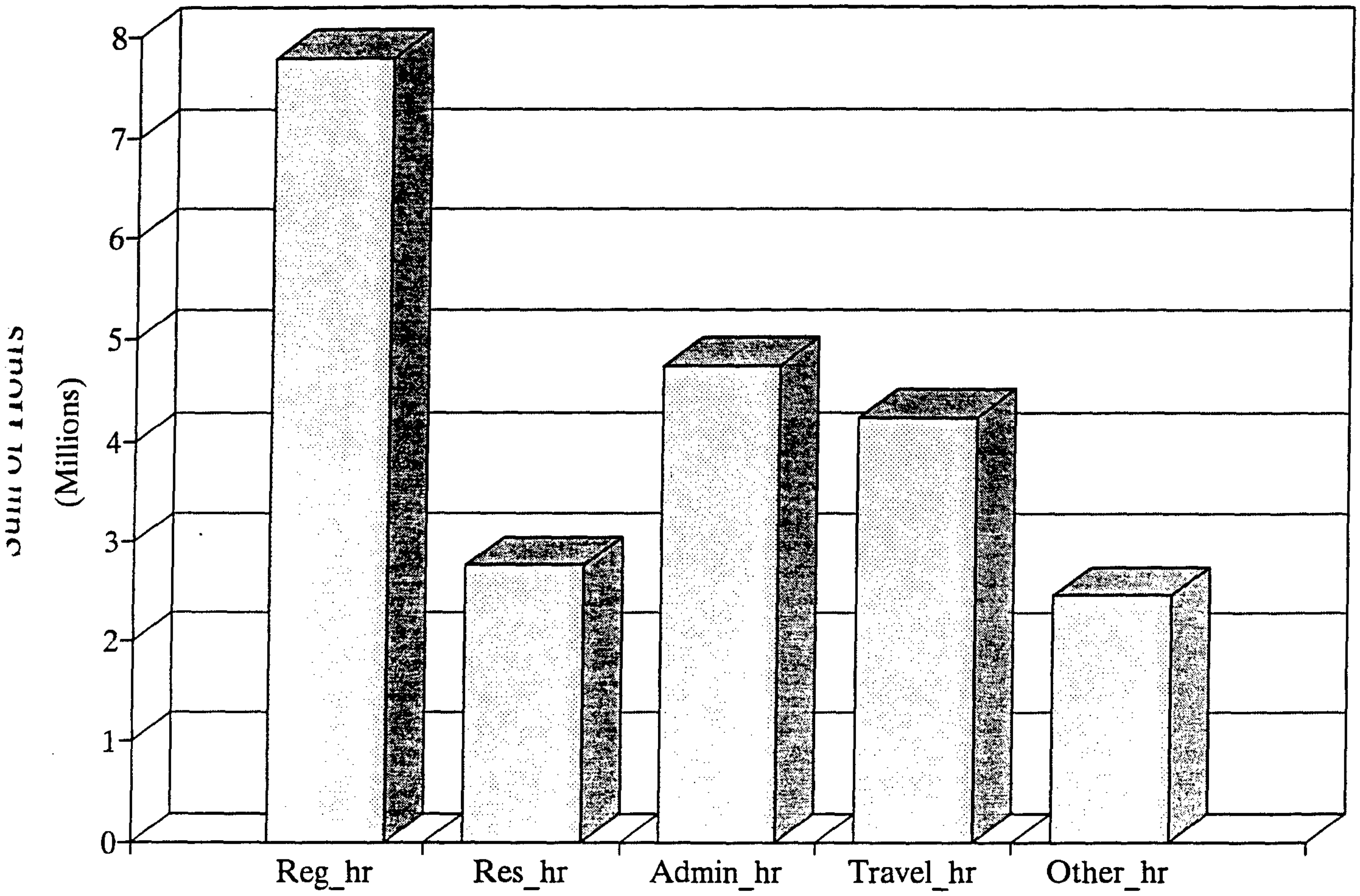


Figure 4.2.3

Port Safety Hours by Service, Foreign Flag, 1989-1993

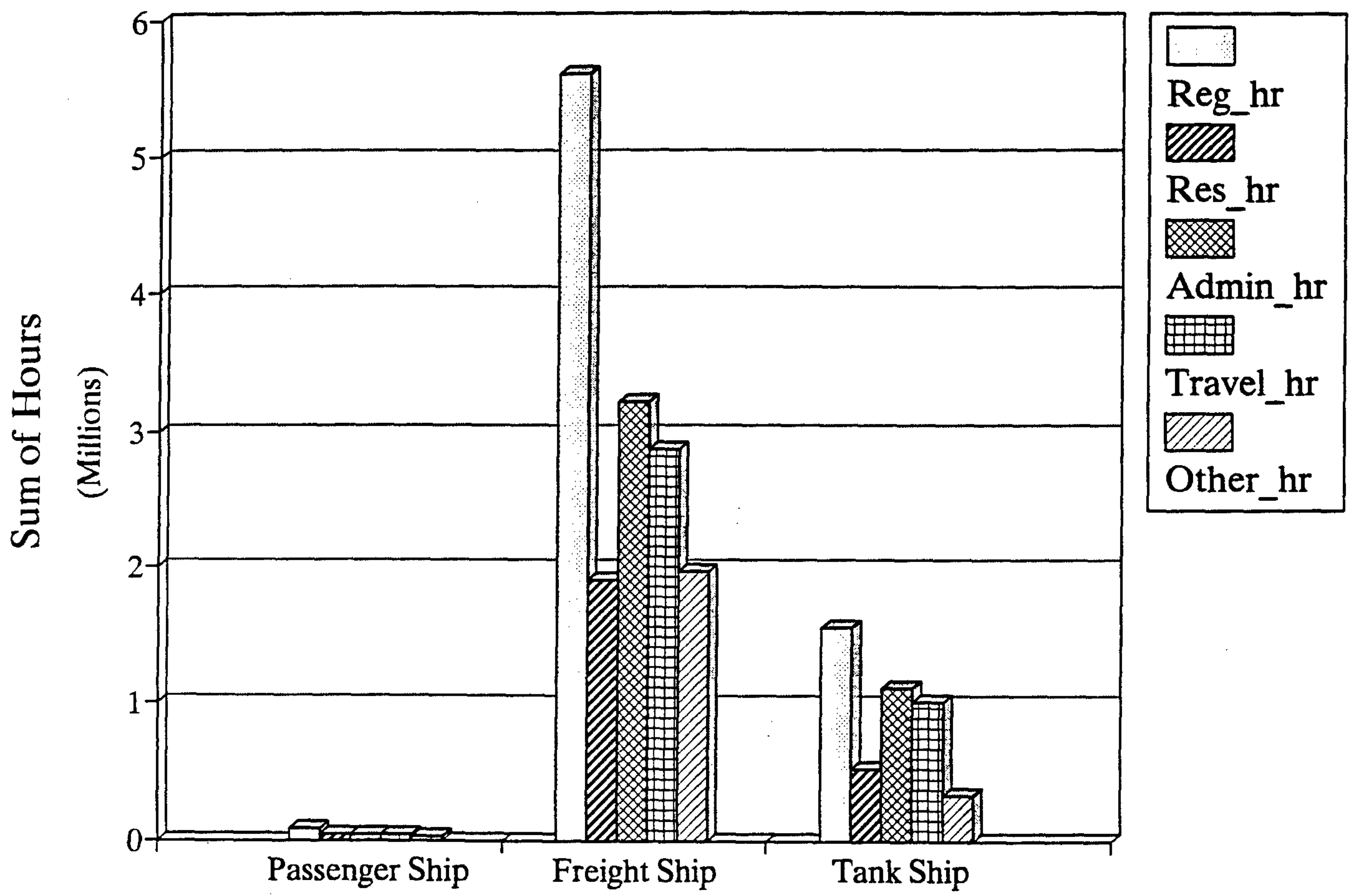


Figure 4.2.4
Average Gross Tonnage, Foreign Flag

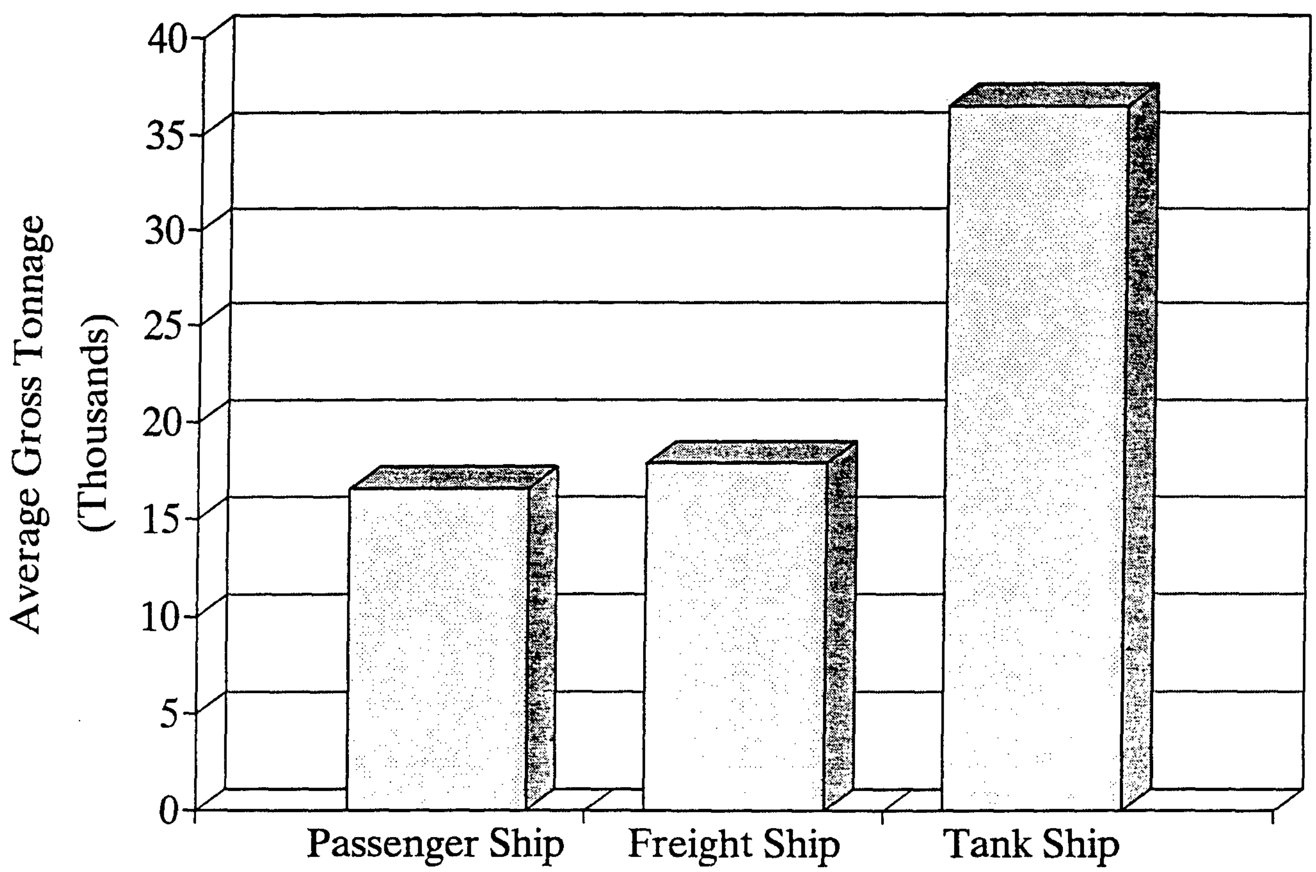


Figure 4.2.5
Average Age by Vessel, Foreign Flag

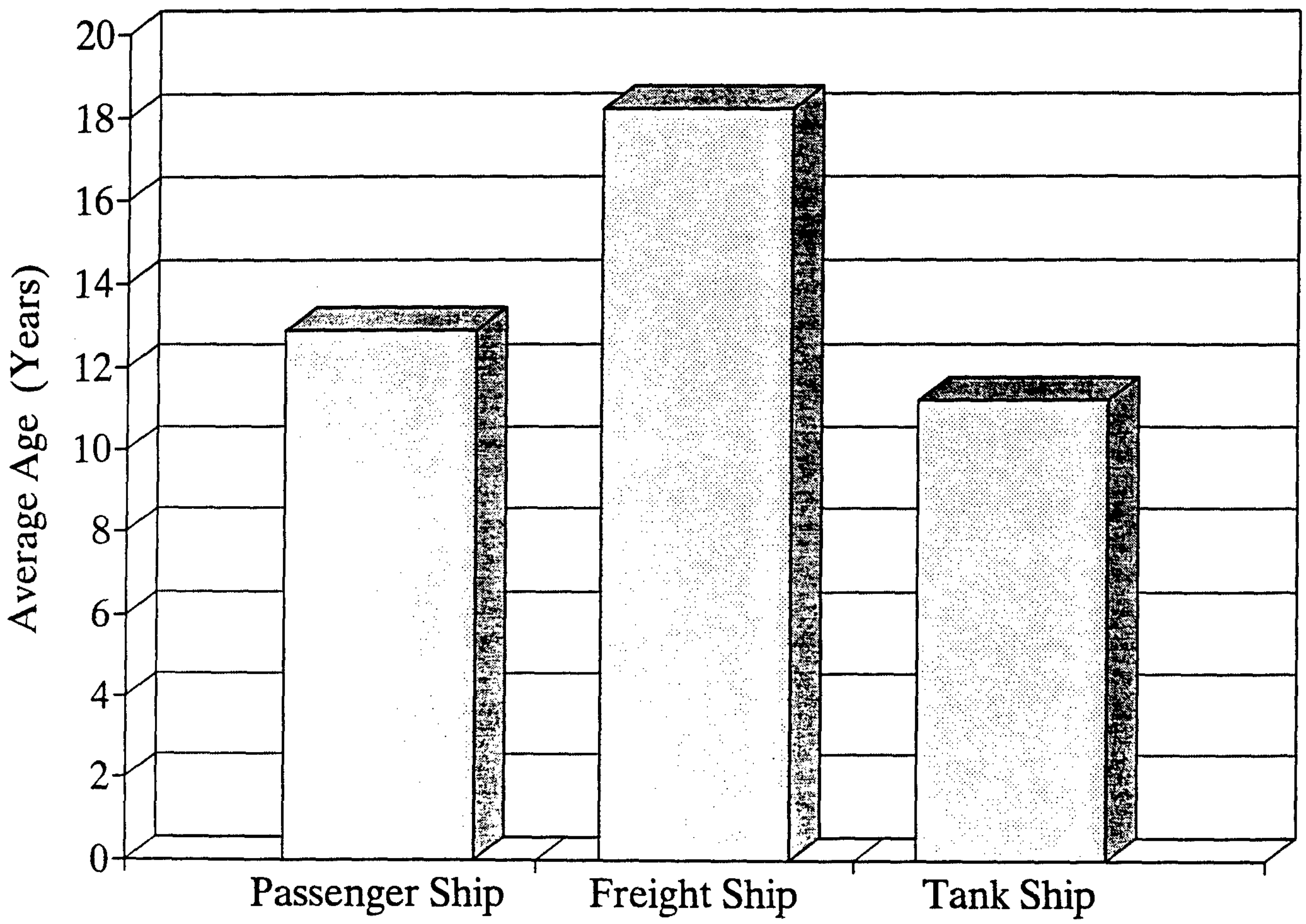


Figure 4.2.6
Average Duration to Personnel Casualty

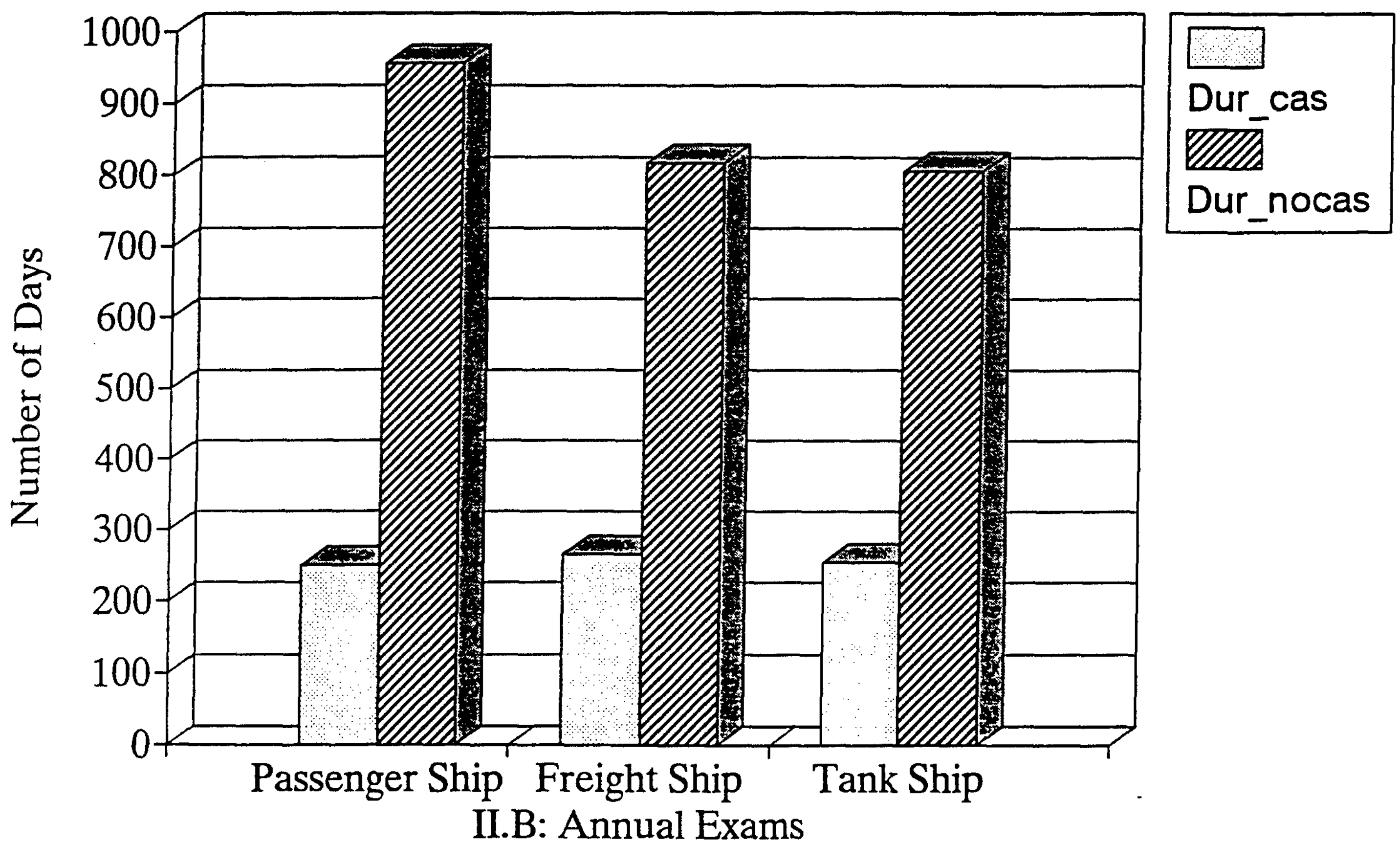
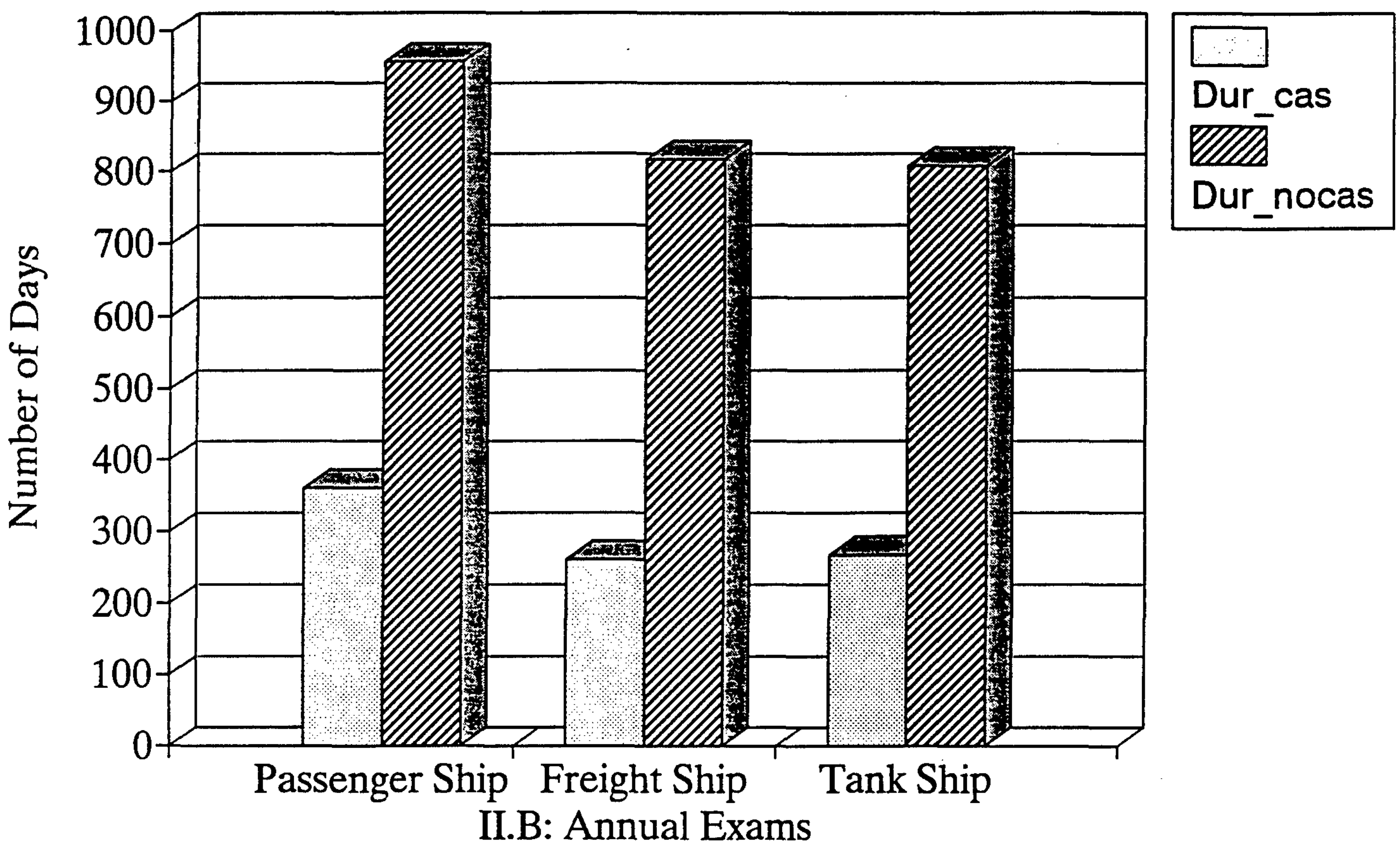


Figure 4.2.7
Average Duration to Pollution Casualty



4.5.2 Level I MOEs for Foreign Flag Deep-Draft Vessels from Poisson Models

The number of Foreign flag deep-draft vessels examined by the USCG far outnumbers the number of U.S. flag deep-draft vessels. But whereas U.S. flag vessels are subject to inspection requirements laid down by the USCG, and hence are subject to thorough safety checks, this is not always true of Foreign flag vessels. The objective of USCG inspections with respect to Foreign flag vessels is to minimize Personnel and Pollution casualties *in U.S. waters*, whereas the objective with regard to U.S. flag vessels is to minimize casualties *anywhere*.

The following analysis attempts to provide answers to two questions. Does the USCG successfully achieve this objective ? If so, is there evidence that the USCG achieves this efficiently ?

The answer to the first question can be answered unconditionally, simply by observing the number of Personnel and Pollution casualties that have occurred since 1991. This measure can be made more sophisticated by dividing it by "traffic" in U.S. waters so as to get a number akin to "accident rate" often used by the Highway Patrol. However, whether the resulting number is "low" may need to be judgmental and subjective. Between 1991 and 1993 there were 30 Deaths and Missing, 97 Injured, and 195 Pollution occurrences. Compared with a traffic of (at least) 8339 Tank ships[17], the casualty rate is fairly impressive. A breakdown by service is more informative. For Freight ships the D&M rate, is 27/8339=.0032, the Injured rate is 44/8339=.0053, and the Pollution rate is 306/8339=.037. For Passenger ships the D&M rate is 0, the Injured rate is 26/200=.130, and the Pollution rate is 34/200=.170. For Tank ships, the D&M rate is 3/2368=.0013, the Injured rate is 27/2368=.011, and the Pollution rate is 195/2368=.082. Clearly, the USCG program of examining Foreign flag vessel is successful in achieving a very low D&M rate (in U.S. waters). However, improvements can and should be made, to lower the Injured and Pollution rates on Passenger vessels, and the Pollution rate on Tank ships.

The answer to the second question is not easy to obtain for two reasons. Compared to U.S. flag vessels, there is much more uncertainty about the state (that is, condition) of a Foreign flag deep-draft vessel that enters U.S. waters than is the case for a U.S. flag deep-draft vessel. Problems in information economics and insurance termed moral hazard and adverse selection become

[17] This is the number of Foreign flag deep-draft vessels examined between 1989 and 1993, so the comparable number during 1991-1993 is somewhat lower. But this is the number of vessels examined, wheras traffic, or vessels traversing U.S. waters with or without an examination, must have been somewhat higher.

critically important. [18] The problem of moral hazard is one where one party to a transaction (the shipowner or operator) may undertake certain actions that affect the other party's (USCG) valuation of the transaction but that the second party cannot monitor or enforce properly. The problem of adverse selection is one where one party to a transaction knows things pertaining to the transaction that are relevant to but unknown by the second party. Foreign flag vessels are subject to widely varying degrees of monitoring and regulation depending on their flag, which can just as easily change from one voyage to another. Moral hazard and adverse selection problems make the distribution of USCG resource hours in examining/monitoring a more complicated and fuzzy task than it is in the case of U.S flag vessels. We believe a complete analysis of the Foreign flag examination program must involve a deep examination of this particular principal-agent problem. We feel this is a question that has more to do with designing optimal enforcement contracts, that is a design of proper incentives, between the USCG and foreign flag shipowners (that at the same time does not upset U.S. corporate interests with whom foreign flag shipowners do business) than just a simple issue of being able to employ USCG resources to unconditionally minimize casualties. According to the present system, the only incentive a foreign flag shipowner has to comply with USCG safety standards is a nominal monetary penalty. Hence the onus is entirely on the USCG to detect and correct problems on Foreign flag vessels. Naturally the use of USCG resources will not be as efficient as in the case where the Foreign flag shipowner "volunteers" correct information. A life insurance company, for example, may sell insurance on the condition that the insured cannot make a claim within the next two years. Those insured who do not expect to live that long will therefore not buy the policy thereby "volunteering" that information. But in the absence of that clause, the insurance company will be forced to expend resources ensuring that the insured is physically fit, which is both expensive and inefficient if it cannot discriminate very well among the millions who wish to buy insurance (which is similar to the situation facing the USCG). However a detailed study leading to the design of optimal incentives is outside the scope of the present study but is probably well worth undertaking in the future especially in light of what the subsequent results indicate about USCG efficiency in conducting its Foreign flag examinations.

Estimates from the Poisson model for Personnel casualties are contained in Table 4.15.1-4.15.3, and for Pollution casualties in Table 4.15.4. These estimates are based on unscaled hours. Although in the Table, statistically significant estimates at 5% and 10% are asterisked, we will take a *t*-value of 1.00 as the critical value, given the discussion in Section 4.4.2 (ii). A high

[18] See e.g. David Kreps, 1990, A Course in Microeconomic Theory, Princeton University Press, for a fairly formal account of the essential ingredients of the economics of uncertainty and information.

degree of risk aversion to pollution by Foreign flag vessels in U.S. waters makes this choice even more justified. Analyses are performed on data sets disaggregated by service. For Freight ships, Table 4.15.1 shows that hours spent by active duty personnel (REG_HR) and hours spent by reserve personnel (RES_HR) are effective in reducing D&M casualties, but these hours are not effective in controlling injuries. Administrative hours appear with a positive sign (just as in the case with unscaled hours for U.S. flag vessels). For Passenger vessels, Table 4.15.2 shows that Regular hours are effective in controlling injuries, but Reserve and Administrative hours have the opposite sign. For Tank ships, Table 4.15.3 shows that Regular hours do seem to reduce injuries, but Administrative hours have the opposite sign. The results for D&M Tank ship casualties may have to do with very few observations having positive values for the dependent variables. This result, where no variables are significant, may be interpreted as a successful job performed by the USCG, since what casualties have occurred are purely random, and cannot be explained by variables such as REG_GT and AGE either. Hence the nonrandom casualties have been prevented due to USCG examinations. The results in Table 4.15.4 indicate that Regular hours are clearly effective in reducing Pollution casualties in vessels of all services, particularly Freight and Tank ships. However Reserve and Administrative hours appear statistically significant with the wrong sign, and that bears explaining. In an effort to investigate further the counterintuitive signs on some resource hour variables, particularly Administrative hours, the same solutions that were tried for the MI cases involving U.S. flag vessels were tried here but are not reported (although are worth discussing). The simultaneous model using predicted resource hour variables, and the model using orthogonalized resource hour variables gave qualitatively very similar results as those discussed above. The models using scaled resource hour variables (by REG_GT) give even more counterintuitive results and, surprisingly, in many cases reverses the correct signs on Regular hours. The results for Foreign flag casualty cases are not nearly robust enough to specification changes as were the corresponding results for U.S. flag vessels. This is not surprising in view of the discussion of the greater uncertainty surrounding the state of Foreign flag vessels. If the unscaled results are to believed, then the USCG is certainly successful in lowering Personnel and Pollution casualties.

4.5.3 Level II MOEs for Foreign Flag Deep-Draft Vessels from Duration Models

The duration data set for Foreign flag vessels contains observations on 12912 Annual Freight Examinations, 3328 Annual Tankship Examinations, and 233 Annual Passenger Examinations. Table 4.16.1 presents estimates for Personnel casualties based on unscaled data. The results echo those of the Poisson model: Regular hours and Reserve hours devoted to Annual Examinations are effective in prolonging time to Personnel casualty for Freight and Tank ships. Administrative hours appear again with the opposite sign. The corresponding estimates with scaled resource

hour variables paint quite a different picture. For Freight ships, four specifications are estimated in Table 4.16.2. The first column includes all three resource hour variables and shows that Regular hours are effective in increasing time to Personnel casualty. However the last three columns with resource hour variables included one at a time reverses this conclusion. The main reason for this is that there is a high degree of correlation among the three resource hour variables, and when correlated variables are dropped (or added), signs on coefficient estimates can easily change. What the estimates in the first and second columns say is the following: "Conditionally on Reserve and Administrative hours, Reserve hours are effective, but on their own, Regular hours do not contribute to prolonging duration to casualty". Reserve hours, on the other hand, are conditionally and unconditionally somewhat effective, while Administrative hours are not effective. For Tank ships, estimates from Table 4.16.3 show that none of the resource hour variables are effective in increasing time to Personnel casualty. For Passenger vessels, estimates in Table 4.16.4 show no statistically significant coefficients, and the *LLR* values show that the fit of the model is poor. We interpret these results in favor of USCG activities - that USCG examinations have successfully reduced the systematic component of the occurrence of Personnel casualties, so that the remaining casualties (8 instances) can be best described as random occurrences.

The duration analysis of Pollution casualties based on unscaled estimates in Table 4.17.1 leads us to the conclusion that there is some weak evidence that Regular hours devoted to Annual Examination of Tank ships is effective in prolonging time to casualty, and Reserve hours are effective for Freight ships and Tank ships. Again Administrative hours appear with the opposite signs. Results based on scaled resource hour variables for Freight ships appear in Table 4.17.2. Again, conditional on Reserve hours and Administrative hours, Regular hours are effective in increasing duration to Pollution casualty, but unconditionally (by itself) Regular hours are not effective. For Tank ships (Table 4.17.3) none of the resource hour variables are seen to be effective. For Passenger ships (Table 4.17.4), we would like to conclude as earlier, that is, Annual Examinations succeed in removing nonrandom occurrences of pollution, so that what remains are random occurrences.

In sum, if the unscaled results are to be believed, the Annual Examinations are effective in prolonging the duration to Personnel and Pollution casualties. But this conclusion should be tempered by the results based on scaled hours. Certainly, the results are not robust to changes in specifications or to scaling of resource hour variables. Our recommendation is to be cautiously optimistic about these results but since they are based on limited information (see below) we withhold judgement till a more complete analysis is possible by combining MSMS data with, say, Lloyd's data pertaining to foreign flag vessels.

Our recommendations for further analysis of the effectiveness of USCG activities on Foreign flag

vessels has to do with the quality and completeness of the data. If we had data on *all* casualties, not just those within U.S. waters, that have occurred, we will get a greater variability in the data that will probably allow statistically more improved inferences. Perhaps the MSMS database could be merged with the Lloyd's database to provide complete information. This is not a trivial task, and requires substantial resources from both the USCG and Lloyd's, but the end results should justify the means. There is considerable incentive for Lloyd's to use MSMS data because of its comprehensive coverage of inspections/boarding/monitoring and casualties of both U.S. and Foreign flag vessels, which will no doubt be useful for Lloyd's insurance purposes. As it stands, the data provides information on only "half" the experiment. There is neither data on the monitoring effort on Foreign flag vessels that occurs outside U.S. waters, nor is there data on the occurrence of casualties outside U.S. waters. We are inferring the effectiveness of USCG activities based on a truncated information set, and clearly the inferences will be much weaker than ones based on the complete information set.

Table 4.15.1

MOEs from a Poisson Model of Personnel Casualties (MINMOD)
PS Cases, Foreign Flag

Cross Section of 8336 Freight Vessels
Dependent variable (y) = Number of personnel affected

rhs variables	lhs variable (y)	
	Deaths and Missing	Injuries
Constant	-3.033 (-1.47)	-3.883 (-2.60)**
Reg_gt	-0.273 (-1.38)	-0.243 (-1.69)*
Reg_hr	-1.309 (-1.75)*	-0.005 (-0.08)
Res_hr	-1.459 (-1.55)	0.113 (0.67)
Admin_hr	2.603 (3.00)**	0.659 (3.10)**
Age	-0.021 (-0.65)	0.0406 (1.99)**
N	8336	8336
k	5	5
LLR	17.109	13.978
$Mad.\ R^2$	0.044	0.024
Obs. with y>0	18	32

Note:
(1) t-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) N=Number of observations, k=number of rhs variables, LLR=Likelihood Ratio Chi-square, $Mad.\ R^2$=Madalla's pseudo R-square.

Table 4.15.2

MOEs from a Poisson Model of Personnel Casualties (MINMOD)
PS Cases, Foreign Flag

Cross Section of 200 Passenger Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable *(y)* Deaths and Missing	Injuries
Constant	No values calculated for deaths and missing due to non-convergence	-39.351 (-8.62)**
Reg_gt		3.437 (8.34)**
Reg_hr		-8.425 (-4.30)**
Res_hr		9.269 (4.95)**
Admin_hr		8.631 (4.30)**
Age		0.069 (3.48)**
N	200	200
k	5	5
LLR		179.644
Mad. R^2		0.732
Obs. with y>0	0	5

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.15.3

MOEs from a Poisson Model of Personnel Casualties (MINMOD)
PS Cases, Foreign Flag

Cross Section of 2368 Tank Vessels
Dependent variable *(y)* = Number of personnel affected

rhs variables	lhs variable *(y)*: Deaths and Missing	lhs variable *(y)*: Injuries
Constant	-14.238 (-1.49)	1.043 (0.44)
Reg_gt	0.570 (0.65)	-0.593 (-2.68)**
Reg_hr	1.559 (1.26)	-0.710 (-1.56)
Res_hr	1.925 (0.88)	0.061 (0.08)
Admin_hr	-2.440 (-1.25)	1.748 (2.88)**
Age	0.067 (0.91)	-0.011 (-0.34)
N	2368	2368
k	5	5
LLR	3.954	23.984
Mad. R^2	0.086	0.077
Obs. with y>0	3	18

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.15.4

MOEs from a Poisson Model of Pollution Casualties (MINMOD)
PS Cases, Foreign Flag

Cross Section of *N* Deep Draft Vessels
Dependent variable *(y)* = Number of Pollution Occurrences

rhs variables	Freight	Passenger	Tank
Constant	-1.609 (-2.84)**	-9.514 (-2.95)**	-0.327 (-0.35)
Reg_gt	-0.281 (-5.20)**	0.758 (2.31)**	-0.306 (-3.50)**
Reg_hr	-0.557 (-2.88)**	-0.780 (1.09)	-0.406 (-2.66)**
Res_hr	0.122 (1.16)	1.260 (1.54)	0.419 (1.57)
Admin_hr	1.502 (6.67)**	0.934 (1.14)	1.294 (5.84)**
Age	0.034 (4.17) **	0.014 (1.19)	0.021 (1.99)**
N	8339	200	2368
k	5	5	5
LLR	179.00	17.429	146.628
Mad. R^2	0.067	0.086	0.105
Obs. with $y>0$	285	25	172

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square, *Mad.* R^2=Madalla's pseudo R-square.

Table 4.16.1

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
PS Cases, Foreign Flag, 1991-1993

Cross Section of *N* II.B Activities (Annual Foreign Vessel Examination)
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injury)

rhs variables	Freight	Passenger	Tank
Constant	7.041 (205.57)**	7.235 (29.93)**	6.822 (84.90)**
Reg_gt	-0.009 (-2.63)**	-0.029 (-1.18)	0.009 (1.25)
Reg_hr	0.047 (1.27)	-0.264 (-1.59)	0.227 (2.67)**
Res_hr	0.971 (2.49)**	1.464 (0.31)	0.120 (1.34)
Admin_hr	-0.932 (-24.47)**	-0.798 (-4.04)**	-1.037 (-12.42)**
Age	0.002 (3.73)**	0.001 (0.66)	.003 (3.74)**
N	12912	233	3328
k	5	5	5
LLR	193.57	6.39	65.40
Obs. with *y*>0	195	8	111

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.16.2

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage, PS Cases, Foreign Flag

Level II.B.1: Cross Section of 12,912 Annual FREIGHT Exams
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injury)

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.821 (965.08)**	6.820 (960.79)**	6.822 (959.22)**	6.820 (963.82)**
Reg_hr	0.354 (2.76)**	-0.226 (-3.89)**		
Res_hr	0.111 (0.73)		0.103 (1.80)	
Admin_hr	-0.780 (-5.62)**			-0.420 (-7.69)**
Age	0.003 (6.59)**	0.002 (6.33)**	0.003 (5.58)**	0.003 (6.80)**
N	12,912	12,912	12,912	12,912
k	4	2	2	2
LLR	15.50	7.13	3.68	13.19
Obs. with *y*>0	195	195	195	195

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.16.3

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. PS Cases. Foreign Flag

Level II.B.2: Cross Section of 3328 Annual TANKSHIP Exams
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injury)

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.795 (591.93)**	6.795 (591.91)**	6.797 (587.16)**	6.795 (589.44)**
Reg_hr	-0.086 (-5.82)**	-0.138 (-3.98)**		
Res_hr	0.187 (0.72)		-0.223 (-1.72)*	
Admin_hr	-0.342 (-1.51)			-0.378 (-2.36)**
Age	0.004 (5.01)**	0.004 (4.79)**	0.003 (4.42)**	0.004 (4.88)**
N	3,328	3,328	3,328	3,328
k	4	2	2	2
LLR	4.50	3.42	2.45	4.10
Obs. with $y>0$	111	111	111	111

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.16.4

MOEs from an Exponential Duration Model of Personnel Casualties (MINMOD)
Hours Scaled by Gross Tonnage. PS Cases, Foreign Flag

Level II.B.3: Cross Section of 233 Annual PASSENGER Exams
Dependent variable *(y)* = Duration to Personnel Casualty (Deaths, Missing, Injury)

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.808 (157.01)**	6.804 (164.03)**	6.805 (162.82)**	6.804 (164.29)**
Reg_hr	-0.969 (-0.32)	-0.149 (-0.49)		
Res_hr	-5.04 (-0.42)		-4.927 (-0.41)	
Admin_hr	0.821 (0.27)			-0.142 (-0.48)
Age	0.002 (0.91)	0.002 (0.89)	0.002 (0.90)	0.002 (0.89)
N	233	233	233	233
k	4	2	2	2
LLR	0.14	0.11	0.11	0.11
Obs. with $y>0$	8	8	8	8

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.17.1

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
PS Cases, Foreign Flag, 1991-1993

Cross Section of *N* II.B Activities (Annual Foreign Vessel Examination)
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Freight	Passenger	Tank
Constant	6.883 (168.25)**	7.487 (26.22)**	6.645 (71.02)**
Reg_gt	0.007 (1.78)*	-0.056 (-1.94)*	0.016 (1.78)*
Reg_hr	-0.010 (-0.25)	-0.157 (-0.96)	0.127 (1.26)
Res_hr	0.049 (1.10)	-0.093 (-0.19)	0.188 (1.76)*
Admin_hr	-0.954 (-22.90)**	-0.879 (-4.34)**	-1.133 (-11.05)**
Age	0.001 (3.08)**	0.001 (0.67)	.001 (1.27)
N	12912	233	3328
k	5	5	5
LLR	221.22	6.41	85.70
Obs. with *y*>0	462	11	318

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.17.2

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. PS Cases, Foreign Flag

Level II.B.1: Cross Section of 12912 Annual FREIGHT Exams
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.810 (914.84)**	6.810 (911.88)**	6.811 (910.20)**	6.810 (913.96)**
Reg_hr	0.372 (2.76)**	-0.294 (-4.15)**		
Res_hr	0.048 (0.29)		0.040 (0.48)	
Admin_hr	-0.883 (-6.04)**			-0.513 (-7.50)**
Age	0.003 (5.39)**	0.003 (5.07)**	0.002 (4.19)**	0.003 (5.56)**
N	12,912	12,912	12,912	12,912
k	4	2	2	2
LLR	19.44	8.62	2.20	17.23
Obs. with *y*>0	462	462	462	462

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.17.3

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. PS Cases. Foreign Flag

Level II.B.2: Cross Section of 3328 Annual TANKSHIP Exams
Dependent variable *(y)* = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.760 (487.43)**	6.760 (488.71)**	6.762 (486.65)**	6.760 (488.16)**
Reg_hr	-0.064 (-3.44)**	-0.120 (-3.32)**		
Res_hr	0.202 (0.67)		-0.199 (-1.07)	
Admin_hr	-0.352 (-1.46)			-0.362 (-2.07)**
Age	0.002 (2.34)**	0.002 (2.15)**	0.002 (1.91)*	0.002 (2.30)**
N	3,328	3,328	3,328	3,328
k	4	2	2	2
LLR	2.72	1.52	0.76	2.42
Obs. with *y*>0	318	318	318	318

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

Table 4.17.4

MOEs from an Exponential Duration Model of Pollution Casualties (MINMOD)
Hours Scaled by Gross Tonnage. PS Cases, Foreign Flag

Level II.B.3: Cross Section of 233 Annual PASSENGER Exams
Dependent variable (y) = Duration to Pollution Casualty

rhs variables	Model 1	Model 2	Model 3	Model 4
Constant	6.795 (158.72)**	6.794 (168.40)**	6.80 (167.01)**	6.794 (168.69)**
Reg_hr	0.496 (0.16)	-0.101 (-0.34)		
Res_hr	-6.165 (-0.45)		-6.147 (-0.45)	
Admin_hr	-0.602 (-0.20)			-0.106 (-0.37)
Age	0.002 (0.83)	0.002 (0.78)	0.002 (0.81)	0.002 (0.79)
N	233	233	233	233
k	4	2	2	2
LLR	0.11	0.08	0.10	0.08
Obs. with y>0	11	11	11	11

Note:
(1) *t*-values in parentheses.
(2) ** indicates statistical significance at the 5% level, and * at the 10% level.
(3) *N*=Number of observations, *k*=number of rhs variables, *LLR*=Likelihood Ratio Chi-square.

5.0 Decision Support Using the Measures of Effectiveness

The overall objective of this study is to provide Measures of Effectiveness (MOEs) of the USCG Marine Inspection and Boarding Program that are based upon objective scientific methods. This component of the study has two sub-objectives: (1) incorporate the functional relationships that produced the MOEs into a easy-to-use, flexible decision aid; and (2) provide a description of the applicability of the MOEs to the allocation of resources to maximize those effectiveness measures.

MOEs are management information. They are actual or appropriate surrogate measures of achievement of goals specified by program management, and are most useful when integrated into improvements in business practices. Justification of programs to Congress is one value MOEs can provide. Improvement in internal management processes such as efficient allocation of inspection resources are another. Section 5.1 will provide an overview of the prototype decision aid implementing the MOEs in a spreadsheet format, while Section 5.2 will discuss methods for incorporating MOEs into the resource allocation process.

5.1 A Prototype Decision Support System

A decision support system (DSS) is an interactive, flexible, and adaptable computer-based information system, designed to support decision making where human judgement and experience are required. It utilizes data, provides an easy user interface and is controlled by, and interacts with, the decision maker allowing for incorporation of his/her insights into the problem solving and decision making process. Tasks such as assessing the effectiveness of USCG activities require both expert judgement and data analysis. The DSS must therefore include models and a modeling capability.

The modeling tool selected for this application was an electronic spreadsheet [Turban, Efrain, 1995, Decision Support and Expert Systems (4th edition) Englewood, N.J.: Prentice Hall] . The modeling capability allows users to create their own models and conduct "what-if" analyses. In addition, reports can be consolidated, and data can be organized in alphabetical or numerical order. Other capabilities include setting up windows for viewing several parts of the spreadsheets simultaneously, and executing mathematical manipulations. These enable the spreadsheet to become an important tool for analysis, planning, and modeling. In addition to the ability of writing models with a spreadsheet, the software includes large numbers of built-in statistical, mathematical, and financial functions. A major capability of spreadsheet programs is that formulas can be embedded using numbers in the spreadsheet; these numbers can be changed and the implications of these changes can immediately be observed and analyzed.

The windows platform was chosen to conform to the availability of USCG hardware. The spreadsheet software selected for the prototype was Microsoft Excel. Excel files can be

converted to Lotus applications, and Excel runs on both Windows and Macintosh platforms.

Rapid prototyping was the methodology used for development of the prototype DSS, and is presented in Figure 5.1, Rapid Prototyping Development Process. This approach permits the creation of the major components of a DSS on a rudimentary basis. The structure of the database and models, and the format of the human-machine interface can be formulated, formalized and implemented quickly, permitting ongoing assessment and revision. The resulting prototype is a tangible product of a project at an early stage; it can be used to retain or increase support of the project. It provides a first system that can be "field tested" - yielding experience in use, and if successful, credibility that the final results of the project will meet its goals. In addition, a prototype can be used to demonstrate the capabilities of decision aids, and point out where human knowledge and judgement are needed.

As part of the rapid prototyping process, various displays were created, implemented in Excel and presented to the USCG for review. The focus of the effort was on models for determining effectiveness as is described in a tutorial companion volume entitled, "Decision Support for Utilizing Measures of Effectiveness." In this DSS tutorial three models from the econometric MOE analysis are presented. The models used in the tutorial are: Model 5 from Table 4.5.2, Model 5 from Table 4.12.3, and Model 4 from Table 4.6.3. An example of the input is displayed in Figure 5.2.

5.2 Analytical Approaches to Resource Allocation

Resource allocation for the Office of Marine Safety can be accomplished by using MOEs as the "benefits" in the development of cost/benefit relationships. Costs can be developed for activities that provide the desired impact on MOEs such as increasing the number of inspections of a certain type. This "activity costing" can be used by program management using the same spreadsheet approach currently used for billet allocation. Basing allocation of resources to MSOs on the risk exposure at the port(s) associated with that MSO, would incorporate MOEs into business practice.

In this section two additional approaches are discussed: (1) Goal Programming, and (2) Convex Resource Allocation.

5.2.1 Goal Programming

Goal programming (GP) formulations set target ranges for the performance in specific program areas. Benefits accrued for achieving the goal are specified as well as penalties for under-achievement and diminished returns for over-achievement. Optimization techniques (e.g., linear programming) are used to decide what combination of activities will best meet the goals, given logistical and budgetary constraints. Appendix E presents a GP formulation of the resource allocation problem.

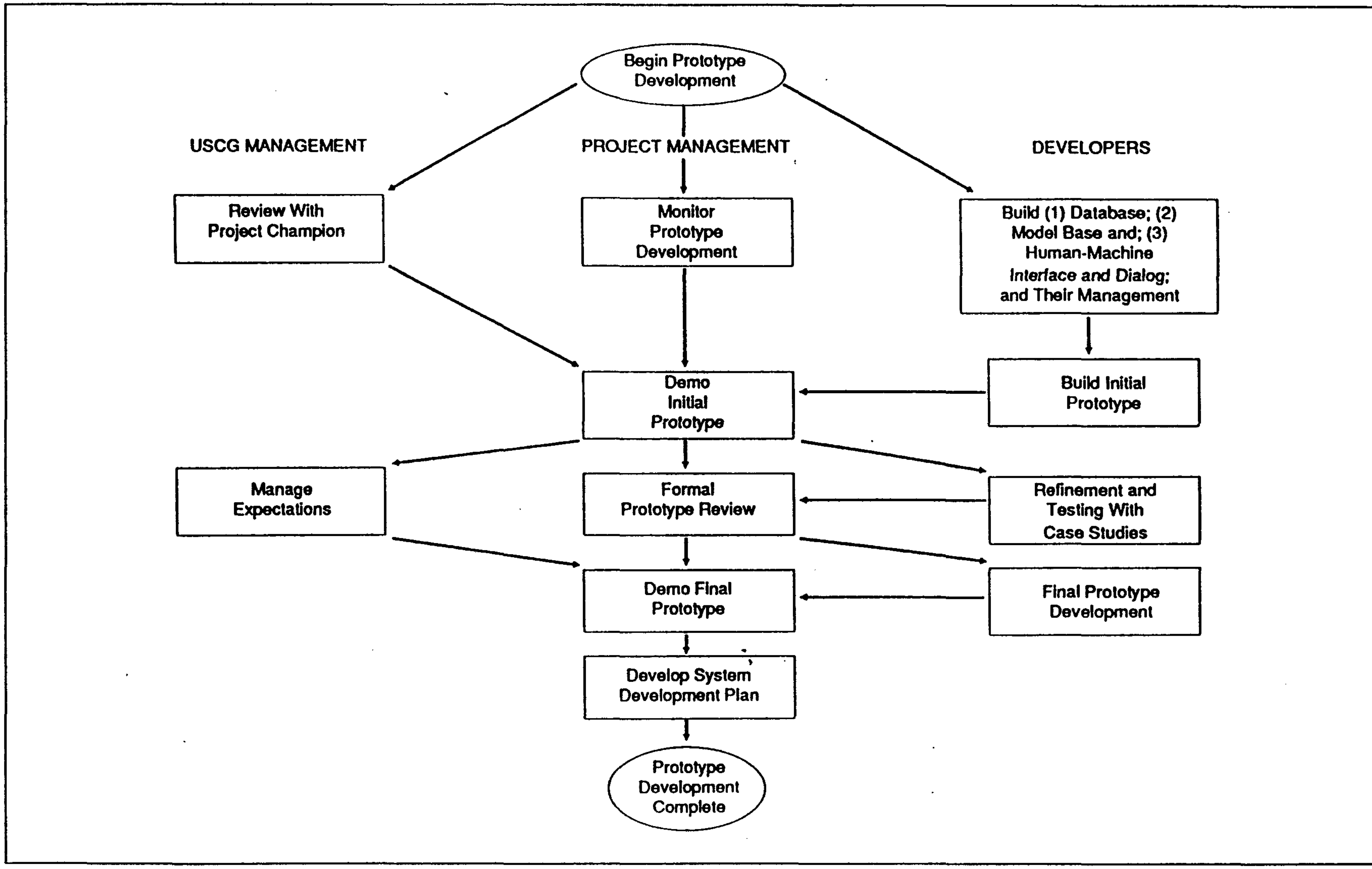


Figure 5.1 Rapid Protoyping Development Process

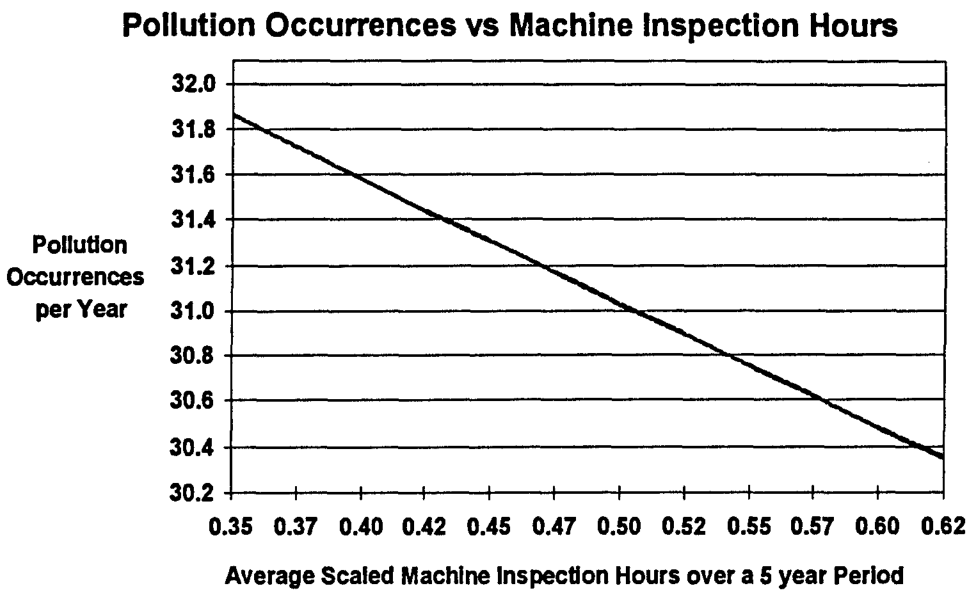


Figure 5.2 Model 5 From Section 4.0 - Table 4.5.2

The benefit of goal programming is the ability to explicitly link stated USCG goals with investment in USCG activities. In addition, this approach can model complex relationships between goals and investments. This ability will be of value when considering decisions that involve infrastructure and organizational design (such as reengineering MSOs). GP provides a framework that permits sophisticated analyses requiring flexibility in the model formulation. It also can provide a means for assessing tradeoffs between safety and environmental issues, by incorporating multiobjectives that may be incommensurate in quantitative terms but must be addressed by program management in an analytical manner. The result may not be the "optimal" solution but a set of "good" alternatives from which a manager can select the best choice.

5.2.2 Application of MOE Analysis to The Design of a USCG Resource Allocation Convex Resource Allocation

In this section, we will discuss the applicability of the current MOE analysis to the problem of allocation of resources to maximize those effectiveness measures.

The Problem

Regular inspections of vessels entering and exiting US ports have been shown to provide a reduction in the probability of casualties and pollution incidents. Increasing the frequency of these inspections should reduce the maritime risk, as should increasing the items to be inspected. These additional activities should be balanced against the increased cost for the USCG and maritime industry of these inspections.

There are different types of inspection resources - USCG inspectors with various qualifications and associated costs, and perhaps contract resources from classification societies. Our discussion here will focus on allocating from a single aggregate set of inspection resources, but the basic reasoning is directly extendable to multiple sets. These resources are assigned to a MSO that services a number of ports. The ability to share resources across MSOs is limited by the cost of moving people around and the stress that places on family life, etc..

It is the responsibility of the vessel operator to contact the USCG when the vessel is due for an inspection or boarding. Alternatively, the USCG through its MSIS system can identify the next port call for a vessel due for inspection. The inspectors decide on which vessels they will board on a daily basis. Lack of information and uncertainties of vessel traffic movements and uncertainties in the time required for certain inspections make it difficult to do long-term scheduling. There is no "user fee" placed upon the vessels to be inspected, and thus no financial means to encourage sharing information with the USCG that would permit better planning.

Much of the time spent in inspection activities consists of getting to the ship, documenting the inspection and inputting the information into MIS systems. Time estimates for inspecting individual marine subsystems have been previously elicited. A standard form is provided for boarding activities - inspection activities are, by their very nature, less pre-defined. The time spent on vessels and their subsystems should be specific to their design, age, nature of cargo and other vessel characteristics.

Through analysis of MOEs, coefficients for models that predict casualty rates have been developed. These models base their predictions on the time spent inspecting various parts of the ship and its operation. These coefficients provide estimates on the marginal change in marine casualty rate from greater inspection time spent on a category of inspection items.

Standard Approaches to Resource Allocation

A convex resource allocation scheme was discussed in some detail in an earlier report entitled "Application of MOEs - The Resource Allocation Business Process". Basically, if

the following information can be developed:

> * a meaningful forecast of vessel traffic by vessel type (age, cargo, size, etc.) can be developed for each MSO,
> * calibrated models that predict the reduction in marine causality by vessel type as a function of frequency of inspection and time invested in the inspection,
> * models that translate marine casualties for ports served by an MSO into consequences cited in the five-year plan for the office of M.

then standard optimization techniques will derive a cost-efficient allocation of USCG inspection resources across MSOs. There is no computational barrier to deriving such an allocation.

Let us layout how we could apply the convex resource allocation methodology with our current analysis. Using the Poisson and duration models developed in the econometric analysis, we can predict the reduction in casualties if inspection hours are increased. These models predict diminishing marginal returns in casualty reduction with increasing levels of inspection. Let us assume they can provide us with predicted casualty reduction for inspection of a particular vessel type (age, tonnage, etc.). The current econometric models can compare casualty rates between freighters, tankers, and passenger ships.

Now, let us make the analogy with investment management. The USCG is actually making a decision on how to invest resources. The alternative investments are MSOs, whose yield on the investment is determined by the amount already invested, and the mix of vessel types that arrive at the MSO. The marginal benefit for the next inspector at an MSO is the marginal benefit of assigning him/her to inspect the vessels that provide the greatest marginal reduction in casualties. If the USCG incrementally assigns resources to the MSO that has the greatest potential reduction in casualties, the USCG will be providing the optimal allocation of inspectors across the MSOs. Because of diminishing marginal returns, a seventh inspector for MSO Baltimore, for example, will not be as valuable as the sixth you just allocated, so it will probably go to some other MSO. When you have exhausted your supply of inspectors to be assigned, the optimal allocation of resources has been made. A slightly more formal mathematical statement of the algorithm is provided in Appendix F.

It is easy to include constraints on minimum and maximum numbers of inspectors to be allocated to any given MSO. You will get the optimal allocation by simply starting with the minimum initial allocation before allocating additional inspectors, and by allocating no more inspectors to MSOs that have reached their maximum.

To develop inspector allocations to meet M-office five-year goals on casualty reduction, we would need forecasted MSO vessel traffic by vessel type for the five-year period. By

incrementally allocating inspectors up to levels of casualty reduction set by the five-year-plan (e.g. 50% reduction in marine casualties in five years - during which time the vessel traffic is expected to increase 20%), the USCG can identify the ultimate resource needs to meet their stated goals.

Because the analysis focused on numbers of casualties, the econometric models do not reflect the ultimate societal values placed on national incidents in certain environmentally or politically sensitive regions. A subjective weight could be placed on the incremental value of reducing incidents in various harbors supported by a given MSO that result in more or fewer resources allocated to the MSO. Alternatively, allocations could be adjusted manually after the fact to account for the vulnerabilities of particular MSO marine environments. Allowing manual adjustments is important for a new business practice, since new processes generally have a few flaws identified during first application.

Can the USCG pursue such an approach with the present analysis?

There are several barriers to applying such techniques to the USCG as our data analysis stands now:

Issue 1. To develop robust coefficient estimates that provide evidence for the effectiveness of inspection programs, the econometric models have been aggregate models. With the aggregate models, we are unable to predict how an increase in inspection activity at an MSO with a given mix of vessel characteristics (and associated risk exposure) will reduce the risk at that MSO.

Issue 2. We have not been able to assess the adequacy of the exposure data that would be available for such a resource allocation model. Obtaining this data has been problematic for both Sandia National Laboratories and the USCG.

Issue 3. It is unclear how well the USCG could forecast vessel traffic rates. Intuitively, if the forecast uncertainty is large, the benefit from any optimal scheme for resource allocation is small.

Issue 4. The option to defer inspections of vessels that have many arrivals at US ports until they arrive at an MSO that has spare inspection capacity is not captured in the previously discussed optimization formulation. To include this feature requires knowledge of how often the USCG would have the opportunity to inspect a vessel, thus requiring a forecast of scheduled port calls by vessel. Note there is currently no mechanism to motivate the vessel operators to provide future vessel schedules. In particular, there is no market incentive to share this (highly proprietary) data with the USCG.

Issue 5. Casualties differ for different vessel types. Tankers have a greater potential for environmental damage than passenger vessels, but passenger vessel casualties may result in greater loss of life. We have not discussed how these qualitatively different impacts could be integrated in a single analysis.

Issue 6. Given the uncertainties that exist in the estimates for marginal benefits, it may not be wise to base the resource investment decision on maximizing the expected benefits. The benefits estimated by the econometric models have some forecast variance associated with them. If the forecast variance is large, the probability of getting little return on your investment is large; i.e. the investment is risky. It may be more prudent to choose an allocation whose yield is less, but whose risk is also less.

For USCG applications of the resource allocation model, we can overcome these barriers and apply the basic allocation scheme described above. That assessment assumes the model is used to provide an initial allocation of inspectors that evolves over time in a market-like manner, as MSOs find they need more or less inspectors to manage to USCG goals.

Issue 1. We can estimate an MSO-specific marginal benefit for the next inspector resource from vessel-type-specific aggregate econometric models. We currently have econometric models which can provide marginal benefit estimates from investing resources in inspecting freight ships, passenger ships and tankers. If a forecast can be provided for the number of freight ships, passenger ships and tankers that arrive at ports for a given MSO, then an MSO-specific marginal benefit model can be developed. It would be the weighted sum of the marginal benefits from inspecting the three types of vessels, where the weights are the number of the three vessel types that can be serviced by a particular MSO.

Issue 2. Perhaps an independent USCG-developed source, or formal purchasing arrangements with the Corps of Engineers or an outside data vendor would be the best approach to address gathering the risk exposure data we need.

Issue 3. For the purposes of developing initial allocations, we should be able to develop effective forecasting schemes for the three vessel types of interest. If a proven product is not available from the private sector, some analysis should be pursued to validate the feasibility and performance of such a forecast.

Issue 4. The issue of multiple arrivals would require both some additional data analysis (to characterize patterns of arrivals by individual vessels, and to identify how often reinspection occurred because of questionable vessel condition flagged

in MSIS) and some simple simulations to develop factors that capture how reinspection and opportunities to defer inspections should affect inspector allocations. These simulations would also allow us to evaluate how the dynamic nature of traffic arrivals may complicate the assignment of inspectors. Our optimization formulation is static. We would expect enough data exists to do the basic analysis.

Issue 5. There are a couple approaches to addressing the problem of non-comparable casualty impacts. One is to *a priori* assign a relative weight for human life vs. environmental damage. The second is to present the decision makers with a tradeoff curve of resource allocations that reflect various weightings between human life and environmental damage, and allow the decision maker to determine the appropriate weighting, given the information provided by the tradeoff curve. We would recommend the latter approach.

Issue 6. We can manage forecast casualty variance by maximizing a weighted sum of the expected marginal returns and the variances associated with those marginal returns. By varying the weights, you are valuing the expected return as more or less important than the likelihood of achieving that return (the variance). Again, we recommend presenting the decision maker with a tradeoff curve that allows the decision maker to choose the proper weighting.

Should the USCG pursue such approaches?

If the USCG is moving towards an "empowered" design for management of the marine inspection business process, the idea of a HQ-level global allocation model doesn't apply. You count on the invisible hand of a market created among competing MSOs to allocate resources effectively, where the return on investment is measured by MOEs for the business process. This assumes MSOs can move people (or motivate people to move) to and from other MSOs, or that contractors can be engaged to handle demand at some market rate. The global allocation models provide a check that the competition between MSOs is not getting in the way of the efficient business operation, and provide some initial allocation to get the game started.

Since the allocation in this case would be a starting point, rather than some control variable, the allocation need not be very precise. Enhancing the spreadsheet-based USCG staffing model, the USCG may get close enough to get the process moving with little additional effort. The current spreadsheet model suffers from a lack of dependence on risk exposure facing the MSO and an inability to reflect the diminishing returns provided by increasing staffing.

The methodology described above addresses these issues. But before the USCG moves

ahead to implementation:

* the ability to forecast MSO vessel traffic rates by vessel type should be validated; and
* the role of intelligent scheduling of vessels for inspection should be understood and its effect reflected as some error factor in the analysis.

Extension of the methodology to handle non-comparable benefits and investment risk has been outlined above, but some additional formality and detail for the methodologies should be developed.

As a final note, if the resource allocation is viewed as support to the Districts, the analysis as laid out would come unbidden and not designed to meet their specific management needs. What may be more supportive of an empowered culture is interviewing Districts and working with them to improve their individual business process. HQ has available data and analysis resources and they come to the Districts to truly "support" them in their hard job of managing their process. By the way, HQ also owns development of the rules of the game and the ultimate quality measures, e.g. MOEs, so the role is not totally one of line support. It would be relatively easy to identify some process improvements that a District might want to investigate with analysis support of HQ. This is consistent with the evolving role of HQ organizations in private industry.

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